knn

April 20, 2020

[3]:
```
from google.colab import drive

drive.mount('/content/drive', force_remount=True)

# enter the foldername in your Drive where you have saved the unzipped
# 'cs231n' folder containing the '.py', 'classifiers' and 'datasets'
# folders.
# e.g. 'cs231n/assignments/assignment1/cs231n/'
FOLDERNAME = 'CS231N/assignment1/cs231n/'

assert FOLDERNAME is not None, "[!] Enter the foldername."

%cd drive/My\ Drive
%cp -r $FOLDERNAME ../../
%cd ../../
%cd cs231n/datasets/
!bash get_datasets.sh
%cd ../../
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id
=947318989803-6bn6qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleusercontent.com&redire
ct_uri=urn%3aietf%3awg%3aoauth%3a2.0%3aoob&response_type=code&scope=email%20http
s%3a%2f%2fwww.googleapis.com%2fauth%2fdocs.test%20https%3a%2f%2fwww.googleapis.c
om%2fauth%2fdrive%20https%3a%2f%2fwww.googleapis.com%2fauth%2fdrive.photos.reado
nly%20https%3a%2f%2fwww.googleapis.com%2fauth%2fpeopleapi.readonly

Enter your authorization code:
ůůůůůůůůůů
Mounted at /content/drive
/content/drive/My Drive
/content
/content/cs231n/datasets
--2020-04-18 19:31:25--  http://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
Resolving www.cs.toronto.edu (www.cs.toronto.edu)... 128.100.3.30
Connecting to www.cs.toronto.edu (www.cs.toronto.edu)|128.100.3.30|:80...
connected.
HTTP request sent, awaiting response... 200 OK
```

```
Length: 170498071 (163M) [application/x-gzip]
Saving to: cifar-10-python.tar.gz

cifar-10-python.tar 100%[===================>] 162.60M  74.8MB/s    in 2.2s

2020-04-18 19:31:27 (74.8 MB/s) - cifar-10-python.tar.gz saved
[170498071/170498071]

cifar-10-batches-py/
cifar-10-batches-py/data_batch_4
cifar-10-batches-py/readme.html
cifar-10-batches-py/test_batch
cifar-10-batches-py/data_batch_3
cifar-10-batches-py/batches.meta
cifar-10-batches-py/data_batch_2
cifar-10-batches-py/data_batch_5
cifar-10-batches-py/data_batch_1
/content
```

1 k-Nearest Neighbor (kNN) exercise

Complete and hand in this completed worksheet (including its outputs and any supporting code outside of the worksheet) with your assignment submission. For more details see the assignments page on the course website.

The kNN classifier consists of two stages:

- During training, the classifier takes the training data and simply remembers it
- During testing, kNN classifies every test image by comparing to all training images and transfering the labels of the k most similar training examples
- The value of k is cross-validated

In this exercise you will implement these steps and understand the basic Image Classification pipeline, cross-validation, and gain proficiency in writing efficient, vectorized code.

[0]:
```
# Run some setup code for this notebook.

import random
import numpy as np
from cs231n.data_utils import load_CIFAR10
import matplotlib.pyplot as plt

# This is a bit of magic to make matplotlib figures appear inline in the␣
 ↪notebook
# rather than in a new window.
%matplotlib inline
plt.rcParams['figure.figsize'] = (10.0, 8.0) # set default size of plots
plt.rcParams['image.interpolation'] = 'nearest'
plt.rcParams['image.cmap'] = 'gray'
```

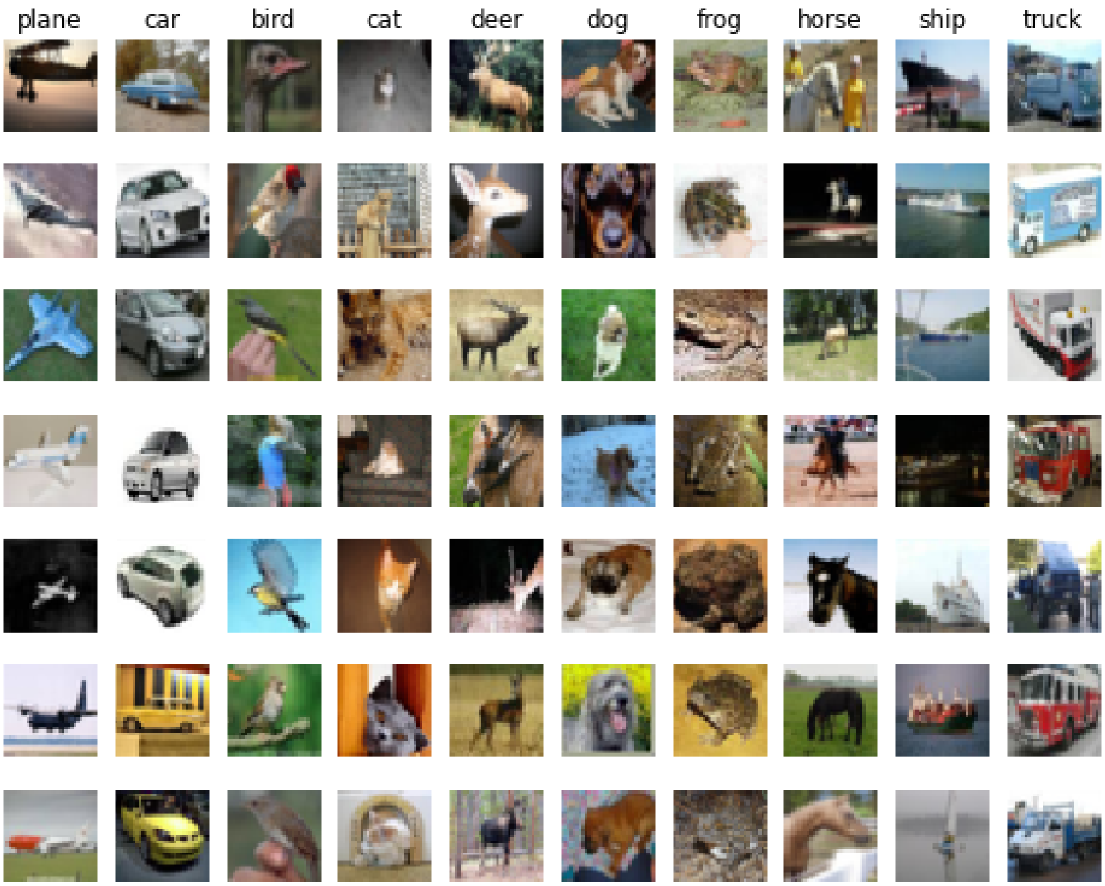
```
# Some more magic so that the notebook will reload external python modules;
# see http://stackoverflow.com/questions/1907993/
 ↪autoreload-of-modules-in-ipython
%load_ext autoreload
%autoreload 2
```

[0]:
```
# Load the raw CIFAR-10 data.
cifar10_dir = 'cs231n/datasets/cifar-10-batches-py'

# Cleaning up variables to prevent loading data multiple times (which may cause␣
 ↪memory issue)
try:
   del X_train, y_train
   del X_test, y_test
   print('Clear previously loaded data.')
except:
   pass

X_train, y_train, X_test, y_test = load_CIFAR10(cifar10_dir)

# As a sanity check, we print out the size of the training and test data.
print('Training data shape: ', X_train.shape)
print('Training labels shape: ', y_train.shape)
print('Test data shape: ', X_test.shape)
print('Test labels shape: ', y_test.shape)
```

```
Training data shape:  (50000, 32, 32, 3)
Training labels shape:  (50000,)
Test data shape:  (10000, 32, 32, 3)
Test labels shape:  (10000,)
```

[0]:
```
# Visualize some examples from the dataset.
# We show a few examples of training images from each class.
classes = ['plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse',␣
 ↪'ship', 'truck']
num_classes = len(classes)
samples_per_class = 7
for y, cls in enumerate(classes):
    idxs = np.flatnonzero(y_train == y)
    idxs = np.random.choice(idxs, samples_per_class, replace=False)
    for i, idx in enumerate(idxs):
        plt_idx = i * num_classes + y + 1
        plt.subplot(samples_per_class, num_classes, plt_idx)
        plt.imshow(X_train[idx].astype('uint8'))
        plt.axis('off')
        if i == 0:
```

```
            plt.title(cls)
plt.show()
```



[0]:

```
# Subsample the data for more efficient code execution in this exercise
num_training = 5000
mask = list(range(num_training))
X_train = X_train[mask]
y_train = y_train[mask]

num_test = 500
mask = list(range(num_test))
X_test = X_test[mask]
y_test = y_test[mask]

# Reshape the image data into rows
X_train = np.reshape(X_train, (X_train.shape[0], -1))
X_test = np.reshape(X_test, (X_test.shape[0], -1))
print(X_train.shape, X_test.shape)
```

```
(5000, 3072) (500, 3072)
```

[0]:
```python
from cs231n.classifiers import KNearestNeighbor

# Create a kNN classifier instance.
# Remember that training a kNN classifier is a noop:
# the Classifier simply remembers the data and does no further processing
classifier = KNearestNeighbor()
classifier.train(X_train, y_train)
```

We would now like to classify the test data with the kNN classifier. Recall that we can break down this process into two steps:

1. First we must compute the distances between all test examples and all train examples.
2. Given these distances, for each test example we find the k nearest examples and have them vote for the label

Lets begin with computing the distance matrix between all training and test examples. For example, if there are **Ntr** training examples and **Nte** test examples, this stage should result in a **Nte x Ntr** matrix where each element (i,j) is the distance between the i-th test and j-th train example.

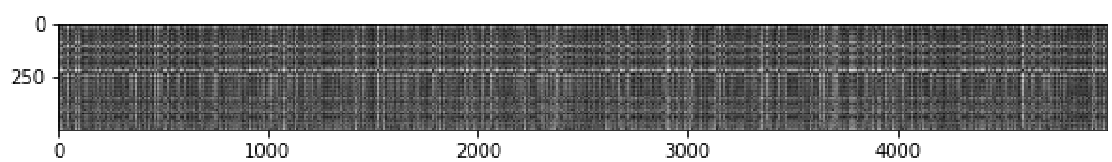
Note: For the three distance computations that we require you to implement in this notebook, you may not use the np.linalg.norm() function that numpy provides.

First, open `cs231n/classifiers/k_nearest_neighbor.py` and implement the function `compute_distances_two_loops` that uses a (very inefficient) double loop over all pairs of (test, train) examples and computes the distance matrix one element at a time.

[0]:
```python
# Open cs231n/classifiers/k_nearest_neighbor.py and implement
# compute_distances_two_loops.

# Test your implementation:
dists = classifier.compute_distances_two_loops(X_test)
print(dists.shape)
```

```
(500, 5000)
```

[0]:
```python
# We can visualize the distance matrix: each row is a single test example and
# its distances to training examples
plt.imshow(dists, interpolation='none')
plt.show()
```



Inline Question 1

Notice the structured patterns in the distance matrix, where some rows or columns are visible brighter. (Note that with the default color scheme black indicates low distances while white indicates high distances.)

- What in the data is the cause behind the distinctly bright rows?
- What causes the columns?

Your Answer : *Using the information above, we can see that darker rows indicate that the i-th test sample was similar to many training examples. Conversely, bright rows indicate that a test point was not similar to many training points. As for columns, we can see that dark columns indicate that the j-th training point was similar to many test points, and lighter columns indicate a lack of said similarity.*

[0]:
```
# Now implement the function predict_labels and run the code below:
# We use k = 1 (which is Nearest Neighbor).
y_test_pred = classifier.predict_labels(dists, k=1)

# Compute and print the fraction of correctly predicted examples
num_correct = np.sum(y_test_pred == y_test)
accuracy = float(num_correct) / num_test
print('Got %d / %d correct => accuracy: %f' % (num_correct, num_test, accuracy))
```

```
Got 137 / 500 correct => accuracy: 0.274000
```

You should expect to see approximately 27% accuracy. Now lets try out a larger `k`, say `k = 5`:

[0]:
```
y_test_pred = classifier.predict_labels(dists, k=5)
num_correct = np.sum(y_test_pred == y_test)
accuracy = float(num_correct) / num_test
print('Got %d / %d correct => accuracy: %f' % (num_correct, num_test, accuracy))
```

```
Got 139 / 500 correct => accuracy: 0.278000
```

You should expect to see a slightly better performance than with `k = 1`.

Inline Question 2

We can also use other distance metrics such as L1 distance. For pixel values $p_{ij}^{(k)}$ at location (i,j) of some image I_k,

the mean μ across all pixels over all images is

$$\mu = \frac{1}{nhw}\sum_{k=1}^{n}\sum_{i=1}^{h}\sum_{j=1}^{w} p_{ij}^{(k)}$$

And the pixel-wise mean μ_{ij} across all images is

$$\mu_{ij} = \frac{1}{n}\sum_{k=1}^{n} p_{ij}^{(k)}.$$

The general standard deviation σ and pixel-wise standard deviation σ_{ij} is defined similarly.

Which of the following preprocessing steps will not change the performance of a Nearest Neighbor classifier that uses L1 distance? Select all that apply. 1. Subtracting the mean μ

$(\tilde{p}_{ij}^{(k)} = p_{ij}^{(k)} - \mu.)$ 2. Subtracting the per pixel mean μ_{ij} $(\tilde{p}_{ij}^{(k)} = p_{ij}^{(k)} - \mu_{ij}.)$ 3. Subtracting the mean μ and dividing by the standard deviation σ. 4. Subtracting the pixel-wise mean μ_{ij} and dividing by the pixel-wise standard deviation σ_{ij}. 5. Rotating the coordinate axes of the data.

$\textit{Your Answer}$: 1, 2, 3, 5

$\textit{Your Explanation}$:

1: When subtracting μ from all pixels, we can see when we then take the difference of individual pixels then the means cancel and we are left with the original expression.

2: By the same mechanism above, we can think of μ as a matrix of the individual pixel means μ_{ij}. When taking the difference of the images in the L1 norm, this new matrix μ cancels.

3: We know that subtracting the mean μ is ok per 1. Dividing by the std dev σ just rescales the distribution. This rescale affects the calculated L1 distances, but not the relative ordering. Therefore, the results don't change.

5: Rotating the axes does not change the differences on a per pixel basis and therefore does not even affect the total L1 distance.

[0]:
```
# Now lets speed up distance matrix computation by using partial vectorization
# with one loop. Implement the function compute_distances_one_loop and run the
# code below:
dists_one = classifier.compute_distances_one_loop(X_test)

# To ensure that our vectorized implementation is correct, we make sure that it
# agrees with the naive implementation. There are many ways to decide whether
# two matrices are similar; one of the simplest is the Frobenius norm. In case
# you haven't seen it before, the Frobenius norm of two matrices is the square
# root of the squared sum of differences of all elements; in other words,␣
↪reshape
# the matrices into vectors and compute the Euclidean distance between them.
difference = np.linalg.norm(dists - dists_one, ord='fro')
print('One loop difference was: %f' % (difference, ))
if difference < 0.001:
    print('Good! The distance matrices are the same')
else:
    print('Uh-oh! The distance matrices are different')
```

```
One loop difference was: 0.000000
Good! The distance matrices are the same
```

[0]:
```
# Now implement the fully vectorized version inside compute_distances_no_loops
# and run the code
dists_two = classifier.compute_distances_no_loops(X_test)

# check that the distance matrix agrees with the one we computed before:
difference = np.linalg.norm(dists - dists_two, ord='fro')
print('No loop difference was: %f' % (difference, ))
if difference < 0.001:
    print('Good! The distance matrices are the same')
else:
    print('Uh-oh! The distance matrices are different')
```

```
No loop difference was: 0.000000
Good! The distance matrices are the same
```

[0]:
```python
# Let's compare how fast the implementations are
def time_function(f, *args):
    """
    Call a function f with args and return the time (in seconds) that it took␣
 ↪to execute.
    """
    import time
    tic = time.time()
    f(*args)
    toc = time.time()
    return toc - tic

two_loop_time = time_function(classifier.compute_distances_two_loops, X_test)
print('Two loop version took %f seconds' % two_loop_time)

one_loop_time = time_function(classifier.compute_distances_one_loop, X_test)
print('One loop version took %f seconds' % one_loop_time)

no_loop_time = time_function(classifier.compute_distances_no_loops, X_test)
print('No loop version took %f seconds' % no_loop_time)

# You should see significantly faster performance with the fully vectorized␣
 ↪implementation!

# NOTE: depending on what machine you're using,
# you might not see a speedup when you go from two loops to one loop,
# and might even see a slow-down.
```

```
Two loop version took 38.801202 seconds
One loop version took 32.162389 seconds
No loop version took 0.554349 seconds
```

1.0.1 Cross-validation

We have implemented the k-Nearest Neighbor classifier but we set the value k = 5 arbitrarily. We will now determine the best value of this hyperparameter with cross-validation.

[0]:
```python
num_folds = 5
k_choices = [1, 3, 5, 8, 10, 12, 15, 20, 50, 100]

X_train_folds = []
y_train_folds = []
################################################################################
# TODO:                                                                        ␣
 ↪#
```

```
# Split up the training data into folds. After splitting, X_train_folds and ␣
 ↪#
# y_train_folds should each be lists of length num_folds, where ␣
 ↪#
# y_train_folds[i] is the label vector for the points in X_train_folds[i]. ␣
 ↪#
# Hint: Look up the numpy array_split function. ␣
 ↪#
################################################################################
# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

y_train_temp = y_train.reshape(-1, 1)
X_train_folds , y_train_folds = np.array_split(X_train, num_folds), np.
 ↪array_split(y_train_temp, num_folds)

# *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

# A dictionary holding the accuracies for different values of k that we find
# when running cross-validation. After running cross-validation,
# k_to_accuracies[k] should be a list of length num_folds giving the different
# accuracy values that we found when using that value of k.
k_to_accuracies = {}


################################################################################
# TODO: ␣
 ↪#
# Perform k-fold cross validation to find the best value of k. For each ␣
 ↪#
# possible value of k, run the k-nearest-neighbor algorithm num_folds times, ␣
 ↪#
# where in each case you use all but one of the folds as training data and the␣
 ↪#
# last fold as a validation set. Store the accuracies for all fold and all ␣
 ↪#
# values of k in the k_to_accuracies dictionary. ␣
 ↪#
################################################################################
# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
# initialize
for k_temp in k_choices:
    k_to_accuracies.setdefault(k_temp, [])
# run kNN
for i in range(num_folds):
    classifier = KNearestNeighbor()
    X_val_train = np.vstack(X_train_folds[0:i] + X_train_folds[i+1:])
```

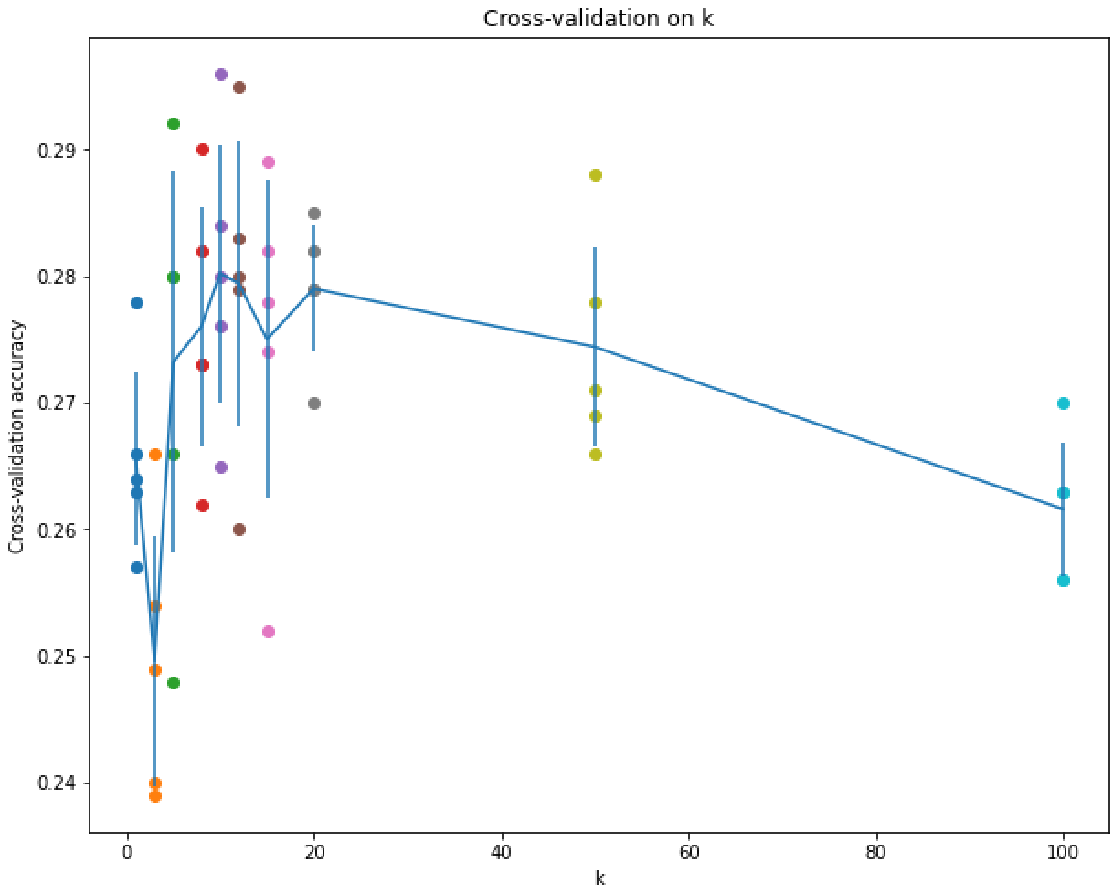
```python
    y_val_train = np.vstack(y_train_folds[0:i] + y_train_folds[i+1:])[:,0]
    classifier.train(X_val_train, y_val_train)
    for k_temp in k_choices:
        predicted_ys = classifier.predict(X_train_folds[i], k=k_temp)
        correct = (predicted_ys == y_train_folds[i][:,0])
        acc = np.mean(correct)
        k_to_accuracies[k_temp] = k_to_accuracies[k_temp] + [acc]

# *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

# Print out the computed accuracies
for k in sorted(k_to_accuracies):
    for accuracy in k_to_accuracies[k]:
        print('k = %d, accuracy = %f' % (k, accuracy))
```

```
k = 1, accuracy = 0.263000
k = 1, accuracy = 0.257000
k = 1, accuracy = 0.264000
k = 1, accuracy = 0.278000
k = 1, accuracy = 0.266000
k = 3, accuracy = 0.239000
k = 3, accuracy = 0.249000
k = 3, accuracy = 0.240000
k = 3, accuracy = 0.266000
k = 3, accuracy = 0.254000
k = 5, accuracy = 0.248000
k = 5, accuracy = 0.266000
k = 5, accuracy = 0.280000
k = 5, accuracy = 0.292000
k = 5, accuracy = 0.280000
k = 8, accuracy = 0.262000
k = 8, accuracy = 0.282000
k = 8, accuracy = 0.273000
k = 8, accuracy = 0.290000
k = 8, accuracy = 0.273000
k = 10, accuracy = 0.265000
k = 10, accuracy = 0.296000
k = 10, accuracy = 0.276000
k = 10, accuracy = 0.284000
k = 10, accuracy = 0.280000
k = 12, accuracy = 0.260000
k = 12, accuracy = 0.295000
k = 12, accuracy = 0.279000
k = 12, accuracy = 0.283000
k = 12, accuracy = 0.280000
k = 15, accuracy = 0.252000
k = 15, accuracy = 0.289000
```

```
k = 15, accuracy = 0.278000
k = 15, accuracy = 0.282000
k = 15, accuracy = 0.274000
k = 20, accuracy = 0.270000
k = 20, accuracy = 0.279000
k = 20, accuracy = 0.279000
k = 20, accuracy = 0.282000
k = 20, accuracy = 0.285000
k = 50, accuracy = 0.271000
k = 50, accuracy = 0.288000
k = 50, accuracy = 0.278000
k = 50, accuracy = 0.269000
k = 50, accuracy = 0.266000
k = 100, accuracy = 0.256000
k = 100, accuracy = 0.270000
k = 100, accuracy = 0.263000
k = 100, accuracy = 0.256000
k = 100, accuracy = 0.263000
```

[0]:

```
# plot the raw observations
for k in k_choices:
    accuracies = k_to_accuracies[k]
    plt.scatter([k] * len(accuracies), accuracies)

# plot the trend line with error bars that correspond to standard deviation
accuracies_mean = np.array([np.mean(v) for k,v in sorted(k_to_accuracies.
 ↪items())])
accuracies_std = np.array([np.std(v) for k,v in sorted(k_to_accuracies.
 ↪items())])
plt.errorbar(k_choices, accuracies_mean, yerr=accuracies_std)
plt.title('Cross-validation on k')
plt.xlabel('k')
plt.ylabel('Cross-validation accuracy')
plt.show()
```



[0]:
```python
# Based on the cross-validation results above, choose the best value for k,
# retrain the classifier using all the training data, and test it on the test
# data. You should be able to get above 28% accuracy on the test data.
best_k = 10

classifier = KNearestNeighbor()
classifier.train(X_train, y_train)
y_test_pred = classifier.predict(X_test, k=best_k)

# Compute and display the accuracy
num_correct = np.sum(y_test_pred == y_test)
accuracy = float(num_correct) / num_test
print('Got %d / %d correct => accuracy: %f' % (num_correct, num_test, accuracy))
```

```
Got 141 / 500 correct => accuracy: 0.282000
```

Inline Question 3

Which of the following statements about k-Nearest Neighbor (k-NN) are true in a classification setting, and for all k? Select all that apply. 1. The decision boundary of the k-NN classifier is linear. 2. The training error of a 1-NN will always be lower than that of 5-NN. 3. The test error of a 1-NN will always be lower than that of a 5-NN. 4. The time needed to classify a test example with the k-NN classifier grows with the size of the training set. 5. None of the above.

$\color{blue}{Your Answer:}$ 2,4

$\color{blue}{Your Explanation:}$

2: At k = 1, we can see that the model will be overfit to the training set, as the matrix will be comparing all training examples to all training examples. This will lead to a training error of 0% (perfect fit) as it just chooses the closest image, which is the same image. With k = 5, the presence of other points in the set of 5 means that the majority label of the set may be different than the label of the closest point. This means that the incorrect label will be chosen, leading to a non-zero training error, which is always greater than the error of the k = 1 model.

4: To classify a test example, we need to create a matrix which has dimensions (# test examples $\times$ # training examples). As a result, we can see that the time needed to fill out the matrix and proceed to the classification step grows with the number of training examples, as it affects the size of the matrix.

---

2 IMPORTANT

This is the end of this question. Please do the following:

1. Click `File -> Save` to make sure the latest checkpoint of this notebook is saved to your Drive.
2. Execute the cell below to download the modified .py files back to your drive.

[0]:
```
import os

FOLDER_TO_SAVE = os.path.join('drive/My Drive/', FOLDERNAME)
FILES_TO_SAVE = ['cs231n/classifiers/k_nearest_neighbor.py']

for files in FILES_TO_SAVE:
  with open(os.path.join(FOLDER_TO_SAVE, '/'.join(files.split('/')[1:])), 'w')␣
 ↪as f:
    f.write(''.join(open(files).readlines()))
```

svm

April 20, 2020

[1]:
```
from google.colab import drive

drive.mount('/content/drive', force_remount=True)

# enter the foldername in your Drive where you have saved the unzipped
# 'cs231n' folder containing the '.py', 'classifiers' and 'datasets'
# folders.
# e.g. 'cs231n/assignments/assignment1/cs231n/'
FOLDERNAME = 'CS231N/assignment1/cs231n/'

assert FOLDERNAME is not None, "[!] Enter the foldername."

%cd drive/My\ Drive
%cp -r $FOLDERNAME ../../
%cd ../../
%cd cs231n/datasets/
!bash get_datasets.sh
%cd ../../
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id
=947318989803-6bn6qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleusercontent.com&redire
ct_uri=urn%3aietf%3awg%3aoauth%3a2.0%3aoob&response_type=code&scope=email%20http
s%3a%2f%2fwww.googleapis.com%2fauth%2fdocs.test%20https%3a%2f%2fwww.googleapis.c
om%2fauth%2fdrive%20https%3a%2f%2fwww.googleapis.com%2fauth%2fdrive.photos.reado
nly%20https%3a%2f%2fwww.googleapis.com%2fauth%2fpeopleapi.readonly

Enter your authorization code:
ůůůůůůůůůů
Mounted at /content/drive
/content/drive/My Drive
/content
/content/cs231n/datasets
--2020-04-20 03:51:55--  http://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
Resolving www.cs.toronto.edu (www.cs.toronto.edu)... 128.100.3.30
Connecting to www.cs.toronto.edu (www.cs.toronto.edu)|128.100.3.30|:80...
connected.
HTTP request sent, awaiting response... 200 OK
```

```
Length: 170498071 (163M) [application/x-gzip]
Saving to: cifar-10-python.tar.gz

cifar-10-python.tar 100%[===================>] 162.60M  15.9MB/s    in 11s

2020-04-20 03:52:07 (14.2 MB/s) - cifar-10-python.tar.gz saved
[170498071/170498071]

cifar-10-batches-py/
cifar-10-batches-py/data_batch_4
cifar-10-batches-py/readme.html
cifar-10-batches-py/test_batch
cifar-10-batches-py/data_batch_3
cifar-10-batches-py/batches.meta
cifar-10-batches-py/data_batch_2
cifar-10-batches-py/data_batch_5
cifar-10-batches-py/data_batch_1
/content
```

1 Multiclass Support Vector Machine exercise

Complete and hand in this completed worksheet (including its outputs and any supporting code outside of the worksheet) with your assignment submission. For more details see the assignments page on the course website.

In this exercise you will:

- implement a fully-vectorized **loss function** for the SVM
- implement the fully-vectorized expression for its **analytic gradient**
- **check your implementation** using numerical gradient
- use a validation set to **tune the learning rate and regularization** strength
- **optimize** the loss function with **SGD**
- **visualize** the final learned weights

[0]:
```python
# Run some setup code for this notebook.

import random
import numpy as np
from cs231n.data_utils import load_CIFAR10
import matplotlib.pyplot as plt

# This is a bit of magic to make matplotlib figures appear inline in the
# notebook rather than in a new window.
%matplotlib inline
plt.rcParams['figure.figsize'] = (10.0, 8.0) # set default size of plots
plt.rcParams['image.interpolation'] = 'nearest'
plt.rcParams['image.cmap'] = 'gray'

# Some more magic so that the notebook will reload external python modules;
```

```
# see http://stackoverflow.com/questions/1907993/
 ↪autoreload-of-modules-in-ipython
%load_ext autoreload
%autoreload 2
```

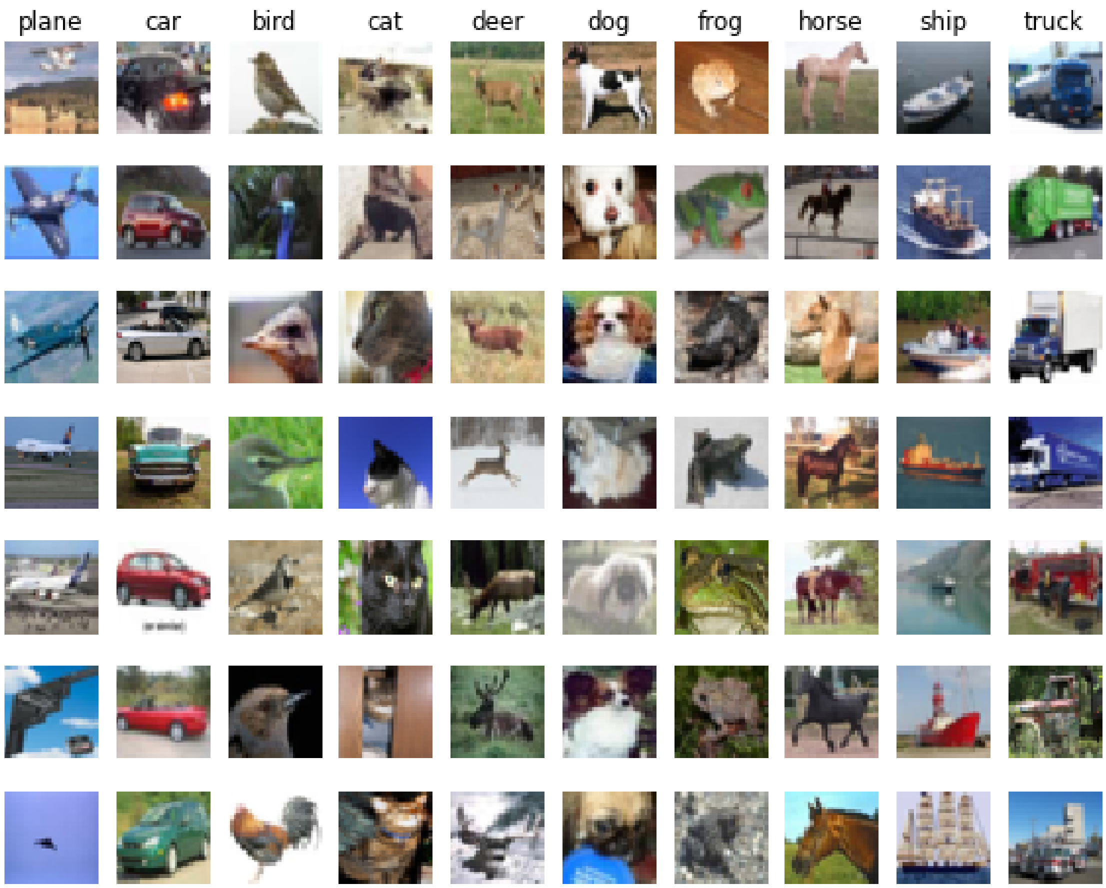
1.1 CIFAR-10 Data Loading and Preprocessing

[3]:
```
# Load the raw CIFAR-10 data.
cifar10_dir = 'cs231n/datasets/cifar-10-batches-py'

# Cleaning up variables to prevent loading data multiple times (which may cause␣
 ↪memory issue)
try:
   del X_train, y_train
   del X_test, y_test
   print('Clear previously loaded data.')
except:
   pass

X_train, y_train, X_test, y_test = load_CIFAR10(cifar10_dir)

# As a sanity check, we print out the size of the training and test data.
print('Training data shape: ', X_train.shape)
print('Training labels shape: ', y_train.shape)
print('Test data shape: ', X_test.shape)
print('Test labels shape: ', y_test.shape)
```

```
Training data shape:  (50000, 32, 32, 3)
Training labels shape:  (50000,)
Test data shape:  (10000, 32, 32, 3)
Test labels shape:  (10000,)
```

[4]:
```
# Visualize some examples from the dataset.
# We show a few examples of training images from each class.
classes = ['plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse',␣
 ↪'ship', 'truck']
num_classes = len(classes)
samples_per_class = 7
for y, cls in enumerate(classes):
    idxs = np.flatnonzero(y_train == y)
    idxs = np.random.choice(idxs, samples_per_class, replace=False)
    for i, idx in enumerate(idxs):
        plt_idx = i * num_classes + y + 1
        plt.subplot(samples_per_class, num_classes, plt_idx)
        plt.imshow(X_train[idx].astype('uint8'))
        plt.axis('off')
```

```
        if i == 0:
            plt.title(cls)
plt.show()
```



[5]:
```
# Split the data into train, val, and test sets. In addition we will
# create a small development set as a subset of the training data;
# we can use this for development so our code runs faster.
num_training = 49000
num_validation = 1000
num_test = 1000
num_dev = 500

# Our validation set will be num_validation points from the original
# training set.
mask = range(num_training, num_training + num_validation)
X_val = X_train[mask]
y_val = y_train[mask]

# Our training set will be the first num_train points from the original
```

```
# training set.
mask = range(num_training)
X_train = X_train[mask]
y_train = y_train[mask]

# We will also make a development set, which is a small subset of
# the training set.
mask = np.random.choice(num_training, num_dev, replace=False)
X_dev = X_train[mask]
y_dev = y_train[mask]

# We use the first num_test points of the original test set as our
# test set.
mask = range(num_test)
X_test = X_test[mask]
y_test = y_test[mask]

print('Train data shape: ', X_train.shape)
print('Train labels shape: ', y_train.shape)
print('Validation data shape: ', X_val.shape)
print('Validation labels shape: ', y_val.shape)
print('Test data shape: ', X_test.shape)
print('Test labels shape: ', y_test.shape)
```

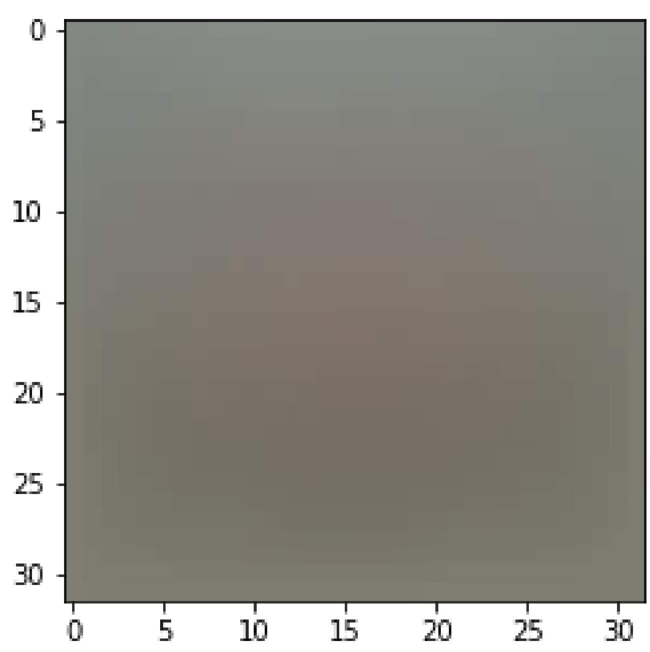
```
Train data shape:  (49000, 32, 32, 3)
Train labels shape:  (49000,)
Validation data shape:  (1000, 32, 32, 3)
Validation labels shape:  (1000,)
Test data shape:  (1000, 32, 32, 3)
Test labels shape:  (1000,)
```

[6]:
```
# Preprocessing: reshape the image data into rows
X_train = np.reshape(X_train, (X_train.shape[0], -1))
X_val = np.reshape(X_val, (X_val.shape[0], -1))
X_test = np.reshape(X_test, (X_test.shape[0], -1))
X_dev = np.reshape(X_dev, (X_dev.shape[0], -1))

# As a sanity check, print out the shapes of the data
print('Training data shape: ', X_train.shape)
print('Validation data shape: ', X_val.shape)
print('Test data shape: ', X_test.shape)
print('dev data shape: ', X_dev.shape)
```

```
Training data shape:  (49000, 3072)
Validation data shape:  (1000, 3072)
Test data shape:  (1000, 3072)
dev data shape:  (500, 3072)
```

[7]:
```python
# Preprocessing: subtract the mean image
# first: compute the image mean based on the training data
mean_image = np.mean(X_train, axis=0)
print(mean_image[:10]) # print a few of the elements
plt.figure(figsize=(4,4))
plt.imshow(mean_image.reshape((32,32,3)).astype('uint8')) # visualize the mean␣
↪image
plt.show()

# second: subtract the mean image from train and test data
X_train -= mean_image
X_val -= mean_image
X_test -= mean_image
X_dev -= mean_image

# third: append the bias dimension of ones (i.e. bias trick) so that our SVM
# only has to worry about optimizing a single weight matrix W.
X_train = np.hstack([X_train, np.ones((X_train.shape[0], 1))])
X_val = np.hstack([X_val, np.ones((X_val.shape[0], 1))])
X_test = np.hstack([X_test, np.ones((X_test.shape[0], 1))])
X_dev = np.hstack([X_dev, np.ones((X_dev.shape[0], 1))])

print(X_train.shape, X_val.shape, X_test.shape, X_dev.shape)
```

```
[130.64189796 135.98173469 132.47391837 130.05569388 135.34804082
 131.75402041 130.96055102 136.14328571 132.47636735 131.48467347]
```



```
(49000, 3073) (1000, 3073) (1000, 3073) (500, 3073)
```

1.2 SVM Classifier

Your code for this section will all be written inside `cs231n/classifiers/linear_svm.py`.

As you can see, we have prefilled the function `svm_loss_naive` which uses for loops to evaluate the multiclass SVM loss function.

[9]:
```
# Evaluate the naive implementation of the loss we provided for you:
import importlib as imp
from cs231n.classifiers.linear_svm import svm_loss_naive
%autoreload 2
import time

# generate a random SVM weight matrix of small numbers
W = np.random.randn(3073, 10) * 0.0001

loss, grad = svm_loss_naive(W, X_dev, y_dev, 0.000005)
print('loss: %f' % (loss, ))
```

```
loss: 8.896029
```

The `grad` returned from the function above is right now all zero. Derive and implement the gradient for the SVM cost function and implement it inline inside the function `svm_loss_naive`. You will find it helpful to interleave your new code inside the existing function.

To check that you have correctly implemented the gradient correctly, you can numerically estimate the gradient of the loss function and compare the numeric estimate to the gradient that you computed. We have provided code that does this for you:

[10]:
```
# Once you've implemented the gradient, recompute it with the code below
# and gradient check it with the function we provided for you

# Compute the loss and its gradient at W.
loss, grad = svm_loss_naive(W, X_dev, y_dev, 0.0, verbose=False)

# Numerically compute the gradient along several randomly chosen dimensions,␣
 ↪and
# compare them with your analytically computed gradient. The numbers should␣
 ↪match
# almost exactly along all dimensions.
from cs231n.gradient_check import grad_check_sparse
f = lambda w: svm_loss_naive(w, X_dev, y_dev, 0.0, verbose=False)[0]
grad_numerical = grad_check_sparse(f, W, grad)

# do the gradient check once again with regularization turned on
# you didn't forget the regularization gradient did you?
loss, grad = svm_loss_naive(W, X_dev, y_dev, 5e1, verbose=False)
f = lambda w: svm_loss_naive(w, X_dev, y_dev, 5e1, verbose=False)[0]
grad_numerical = grad_check_sparse(f, W, grad)
```

```
numerical: -11.404895 analytic: -11.404895, relative error: 7.115928e-12
numerical: -39.915996 analytic: -39.915996, relative error: 5.337616e-12
numerical: -13.860263 analytic: -13.860263, relative error: 5.819829e-12
numerical: -8.959144 analytic: -8.959144, relative error: 2.580286e-11
numerical: 30.513244 analytic: 30.513244, relative error: 1.317188e-11
numerical: 9.501030 analytic: 9.501030, relative error: 5.155065e-11
numerical: 9.867873 analytic: 9.867873, relative error: 2.578253e-12
numerical: 21.362991 analytic: 21.362991, relative error: 3.091226e-12
numerical: 0.990845 analytic: 0.990845, relative error: 2.723793e-10
numerical: 8.758548 analytic: 8.758548, relative error: 4.122876e-11
numerical: -4.263222 analytic: -4.263222, relative error: 1.441168e-11
numerical: 36.005168 analytic: 36.005168, relative error: 8.861762e-12
numerical: 14.910136 analytic: 14.910136, relative error: 9.998677e-12
numerical: 11.314748 analytic: 11.314748, relative error: 5.568606e-12
numerical: 6.421308 analytic: 6.421308, relative error: 4.157059e-11
numerical: -9.856624 analytic: -9.856624, relative error: 1.731496e-11
numerical: -12.856590 analytic: -12.872747, relative error: 6.279610e-04
numerical: -6.252521 analytic: -6.252521, relative error: 5.039623e-11
numerical: -24.149041 analytic: -24.149041, relative error: 1.453552e-11
numerical: -5.749238 analytic: -5.734299, relative error: 1.300828e-03
```

[11]:
```python
# Next implement the function svm_loss_vectorized; for now only compute the
 ↪loss;
# we will implement the gradient in a moment.
tic = time.time()
loss_naive, grad_naive = svm_loss_naive(W, X_dev, y_dev, 0.000005)
toc = time.time()
print('Naive loss: %e computed in %fs' % (loss_naive, toc - tic))

from cs231n.classifiers.linear_svm import svm_loss_vectorized
tic = time.time()
loss_vectorized, _ = svm_loss_vectorized(W, X_dev, y_dev, 0.000005,
 ↪verbose=False)
toc = time.time()
print('Vectorized loss: %e computed in %fs' % (loss_vectorized, toc - tic))

# The losses should match but your vectorized implementation should be much
 ↪faster.
print('difference: %f' % (loss_naive - loss_vectorized))
```

```
Naive loss: 8.896029e+00 computed in 0.144502s
Vectorized loss: 8.896029e+00 computed in 0.014922s
difference: -0.000000
```

Inline Question 1

It is possible that once in a while a dimension in the gradcheck will not match exactly. What could such a discrepancy be caused by? Is it a reason for concern? What is a simple example in one dimension where a gradient check could fail? How would change the margin affect of the frequency of this happening? *Hint: the SVM loss function is not strictly speaking differentiable*

Your Answer : We know that loss functions are designed to be differentiable or semi-differentiable estimations of a non-differentiable function such as Heaviside step. For example, ReLU is a frequently used loss function but is not differentiable at x = 0. As such the numerical and analytical answers for the gradient will be different. We can see that this is the case in the results above: around x=0, the relative error is usually higher than at x points farther from 0.

[12]:
```python
# Complete the implementation of svm_loss_vectorized, and compute the gradient
# of the loss function in a vectorized way.

# The naive implementation and the vectorized implementation should match, but
# the vectorized version should still be much faster.
tic = time.time()
_, grad_naive = svm_loss_naive(W, X_dev, y_dev, 0.000005)
toc = time.time()
print('Naive loss and gradient: computed in %fs' % (toc - tic))

tic = time.time()
_, grad_vectorized = svm_loss_vectorized(W, X_dev, y_dev, 0.000005)
toc = time.time()
print('Vectorized loss and gradient: computed in %fs' % (toc - tic))

# The loss is a single number, so it is easy to compare the values computed
# by the two implementations. The gradient on the other hand is a matrix, so
# we use the Frobenius norm to compare them.
difference = np.linalg.norm(grad_naive - grad_vectorized, ord='fro')
print('difference: %f' % difference)
```

```
Naive loss and gradient: computed in 0.144390s
Vectorized loss and gradient: computed in 0.011132s
difference: 0.000000
```

1.2.1 Stochastic Gradient Descent

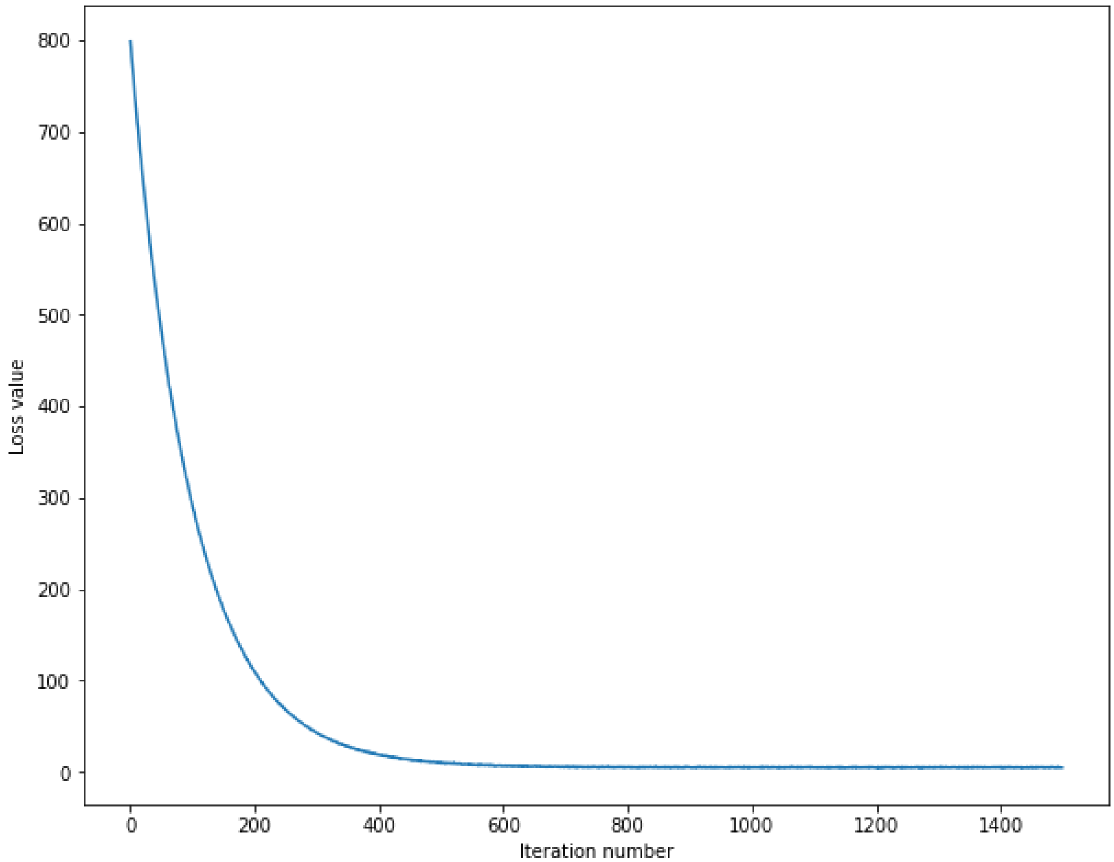
We now have vectorized and efficient expressions for the loss, the gradient and our gradient matches the numerical gradient. We are therefore ready to do SGD to minimize the loss. Your code for this part will be written inside `cs231n/classifiers/linear_classifier.py`.

[13]:
```python
# In the file linear_classifier.py, implement SGD in the function
# LinearClassifier.train() and then run it with the code below.
from cs231n.classifiers import LinearSVM

svm = LinearSVM()
tic = time.time()
loss_hist = svm.train(X_train, y_train, learning_rate=1e-7, reg=2.5e4,
                      num_iters=1500, verbose=True)
toc = time.time()
print('That took %fs' % (toc - tic))
```

```
iteration 0 / 1500: loss 798.549859
iteration 100 / 1500: loss 289.836310
iteration 200 / 1500: loss 109.665026
iteration 300 / 1500: loss 43.034211
iteration 400 / 1500: loss 19.080423
iteration 500 / 1500: loss 9.788143
iteration 600 / 1500: loss 6.755816
iteration 700 / 1500: loss 6.213017
iteration 800 / 1500: loss 5.675527
iteration 900 / 1500: loss 5.360775
iteration 1000 / 1500: loss 5.461346
iteration 1100 / 1500: loss 5.250511
iteration 1200 / 1500: loss 5.162550
iteration 1300 / 1500: loss 5.342135
iteration 1400 / 1500: loss 5.290634
That took 7.669931s
```

[14]:

```python
# A useful debugging strategy is to plot the loss as a function of
# iteration number:
plt.plot(loss_hist)
plt.xlabel('Iteration number')
plt.ylabel('Loss value')
plt.show()
```



[15]:
```
# Write the LinearSVM.predict function and evaluate the performance on both the
# training and validation set
y_train_pred = svm.predict(X_train)
print('training accuracy: %f' % (np.mean(y_train == y_train_pred), ))
y_val_pred = svm.predict(X_val)
print('validation accuracy: %f' % (np.mean(y_val == y_val_pred), ))
```

```
training accuracy: 0.367510
validation accuracy: 0.379000
```

[16]:
```
# Use the validation set to tune hyperparameters (regularization strength and
# learning rate). You should experiment with different ranges for the learning
# rates and regularization strengths; if you are careful you should be able to
# get a classification accuracy of about 0.39 on the validation set.

# Note: you may see runtime/overflow warnings during hyper-parameter search.
# This may be caused by extreme values, and is not a bug.

# results is dictionary mapping tuples of the form
# (learning_rate, regularization_strength) to tuples of the form
```

```
# (training_accuracy, validation_accuracy). The accuracy is simply the fraction
# of data points that are correctly classified.
results = {}
best_val = -1   # The highest validation accuracy that we have seen so far.
best_svm = None # The LinearSVM object that achieved the highest validation␣
 ↪rate.

################################################################################
# TODO:                                                                       ␣
 ↪#
# Write code that chooses the best hyperparameters by tuning on the validation␣
 ↪#
# set. For each combination of hyperparameters, train a linear SVM on the     ␣
 ↪#
# training set, compute its accuracy on the training and validation sets, and ␣
 ↪#
# store these numbers in the results dictionary. In addition, store the best  ␣
 ↪#
# validation accuracy in best_val and the LinearSVM object that achieves this ␣
 ↪#
# accuracy in best_svm.                                                       ␣
 ↪#
#                                                                             ␣
 ↪#
# Hint: You should use a small value for num_iters as you develop your        ␣
 ↪#
# validation code so that the SVMs don't take much time to train; once you are␣
 ↪#
# confident that your validation code works, you should rerun the validation  ␣
 ↪#
# code with a larger value for num_iters.                                     ␣
 ↪#
################################################################################

# Provided as a reference. You may or may not want to change these␣
 ↪hyperparameters
learning_rates = [1.7e-7, 1.8e-7, 1.9e-7]
regularization_strengths = [(1.3+i*0.1)*1e4 for i in range(-3,3)] + [(2+0.
 ↪1*i)*1e4 for i in range(-3,3)]

# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

for r in regularization_strengths:
    for l in learning_rates:
        svm = LinearSVM();
        loss_hist = svm.train(X_train, y_train, l, r, num_iters=2000)
```

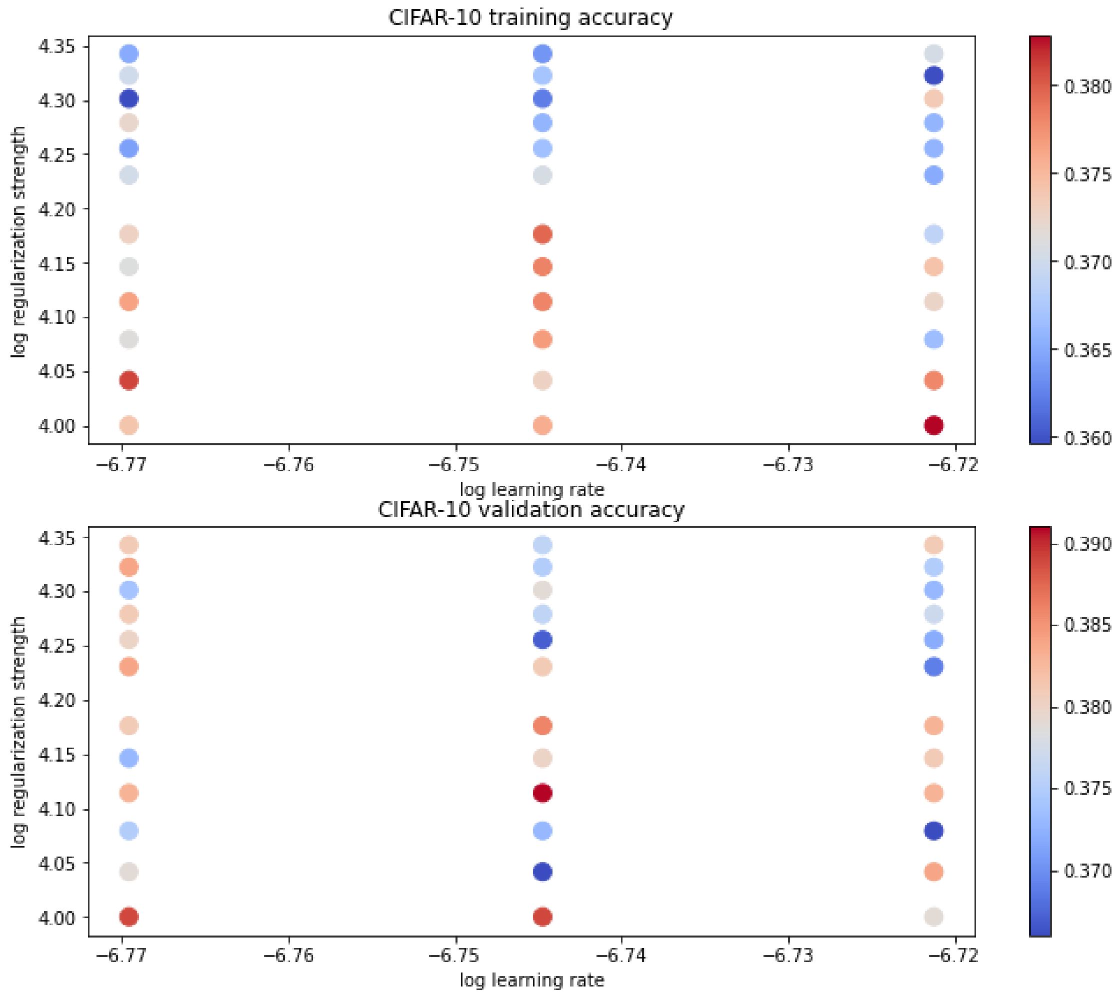
```python
        y_train_pred = svm.predict(X_train)
        y_val_pred = svm.predict(X_val)
        train_accuracy = np.mean(y_train_pred == y_train)
        val_accuracy = np.mean(y_val_pred == y_val)
        results[(l, r)] = train_accuracy, val_accuracy
        if val_accuracy > best_val:
            best_val = val_accuracy
            best_svm = svm

# *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

# Print out results.
for lr, reg in sorted(results):
    train_accuracy, val_accuracy = results[(lr, reg)]
    print('lr %e reg %e train accuracy: %f val accuracy: %f' % (
                lr, reg, train_accuracy, val_accuracy))

print('best validation accuracy achieved during cross-validation: %f' %␣
 ↪best_val)
```

```
lr 1.700000e-07 reg 1.000000e+04 train accuracy: 0.374082 val accuracy: 0.389000
lr 1.700000e-07 reg 1.100000e+04 train accuracy: 0.381102 val accuracy: 0.379000
lr 1.700000e-07 reg 1.200000e+04 train accuracy: 0.371367 val accuracy: 0.375000
lr 1.700000e-07 reg 1.300000e+04 train accuracy: 0.376551 val accuracy: 0.383000
lr 1.700000e-07 reg 1.400000e+04 train accuracy: 0.371184 val accuracy: 0.373000
lr 1.700000e-07 reg 1.500000e+04 train accuracy: 0.372898 val accuracy: 0.381000
lr 1.700000e-07 reg 1.700000e+04 train accuracy: 0.370286 val accuracy: 0.384000
lr 1.700000e-07 reg 1.800000e+04 train accuracy: 0.364347 val accuracy: 0.380000
lr 1.700000e-07 reg 1.900000e+04 train accuracy: 0.372245 val accuracy: 0.381000
lr 1.700000e-07 reg 2.000000e+04 train accuracy: 0.359592 val accuracy: 0.374000
lr 1.700000e-07 reg 2.100000e+04 train accuracy: 0.370102 val accuracy: 0.384000
lr 1.700000e-07 reg 2.200000e+04 train accuracy: 0.365122 val accuracy: 0.381000
lr 1.800000e-07 reg 1.000000e+04 train accuracy: 0.375837 val accuracy: 0.389000
lr 1.800000e-07 reg 1.100000e+04 train accuracy: 0.372939 val accuracy: 0.366000
lr 1.800000e-07 reg 1.200000e+04 train accuracy: 0.376898 val accuracy: 0.373000
lr 1.800000e-07 reg 1.300000e+04 train accuracy: 0.378122 val accuracy: 0.391000
lr 1.800000e-07 reg 1.400000e+04 train accuracy: 0.378265 val accuracy: 0.380000
lr 1.800000e-07 reg 1.500000e+04 train accuracy: 0.379612 val accuracy: 0.386000
lr 1.800000e-07 reg 1.700000e+04 train accuracy: 0.370592 val accuracy: 0.381000
lr 1.800000e-07 reg 1.800000e+04 train accuracy: 0.366755 val accuracy: 0.367000
lr 1.800000e-07 reg 1.900000e+04 train accuracy: 0.365776 val accuracy: 0.376000
lr 1.800000e-07 reg 2.000000e+04 train accuracy: 0.362306 val accuracy: 0.379000
lr 1.800000e-07 reg 2.100000e+04 train accuracy: 0.367122 val accuracy: 0.375000
lr 1.800000e-07 reg 2.200000e+04 train accuracy: 0.363714 val accuracy: 0.376000
lr 1.900000e-07 reg 1.000000e+04 train accuracy: 0.382837 val accuracy: 0.379000
lr 1.900000e-07 reg 1.100000e+04 train accuracy: 0.377959 val accuracy: 0.384000
lr 1.900000e-07 reg 1.200000e+04 train accuracy: 0.366490 val accuracy: 0.366000
```

```
lr 1.900000e-07 reg 1.300000e+04 train accuracy: 0.372510 val accuracy: 0.383000
lr 1.900000e-07 reg 1.400000e+04 train accuracy: 0.374224 val accuracy: 0.381000
lr 1.900000e-07 reg 1.500000e+04 train accuracy: 0.368816 val accuracy: 0.383000
lr 1.900000e-07 reg 1.700000e+04 train accuracy: 0.365061 val accuracy: 0.369000
lr 1.900000e-07 reg 1.800000e+04 train accuracy: 0.365694 val accuracy: 0.372000
lr 1.900000e-07 reg 1.900000e+04 train accuracy: 0.365837 val accuracy: 0.377000
lr 1.900000e-07 reg 2.000000e+04 train accuracy: 0.373612 val accuracy: 0.373000
lr 1.900000e-07 reg 2.100000e+04 train accuracy: 0.359694 val accuracy: 0.375000
lr 1.900000e-07 reg 2.200000e+04 train accuracy: 0.370571 val accuracy: 0.381000
best validation accuracy achieved during cross-validation: 0.391000
```

[17]:

```python
# Visualize the cross-validation results
import math
import pdb

# pdb.set_trace()

x_scatter = [math.log10(x[0]) for x in results]
y_scatter = [math.log10(x[1]) for x in results]

# plot training accuracy
marker_size = 100
colors = [results[x][0] for x in results]
plt.subplot(2, 1, 1)
plt.tight_layout(pad=3)
plt.scatter(x_scatter, y_scatter, marker_size, c=colors, cmap=plt.cm.coolwarm)
plt.colorbar()
plt.xlabel('log learning rate')
plt.ylabel('log regularization strength')
plt.title('CIFAR-10 training accuracy')

# plot validation accuracy
colors = [results[x][1] for x in results] # default size of markers is 20
plt.subplot(2, 1, 2)
plt.scatter(x_scatter, y_scatter, marker_size, c=colors, cmap=plt.cm.coolwarm)
plt.colorbar()
plt.xlabel('log learning rate')
plt.ylabel('log regularization strength')
plt.title('CIFAR-10 validation accuracy')
plt.show()
```



[18]:
```
# Evaluate the best svm on test set
y_test_pred = best_svm.predict(X_test)
test_accuracy = np.mean(y_test == y_test_pred)
print('linear SVM on raw pixels final test set accuracy: %f' % test_accuracy)
```

```
linear SVM on raw pixels final test set accuracy: 0.360000
```

[19]:
```
# Visualize the learned weights for each class.
# Depending on your choice of learning rate and regularization strength, these
 ↪may
# or may not be nice to look at.
w = best_svm.W[:-1,:] # strip out the bias
w = w.reshape(32, 32, 3, 10)
w_min, w_max = np.min(w), np.max(w)
classes = ['plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse',
 ↪'ship', 'truck']
```

```python
for i in range(10):
    plt.subplot(2, 5, i + 1)

    # Rescale the weights to be between 0 and 255
    wimg = 255.0 * (w[:, :, :, i].squeeze() - w_min) / (w_max - w_min)
    plt.imshow(wimg.astype('uint8'))
    plt.axis('off')
    plt.title(classes[i])
```

Inline question 2

Describe what your visualized SVM weights look like, and offer a brief explanation for why they look they way that they do.

$\color{blue}{Your Answer :}$ *We can see a vague impression of each labeled object in its respective SVM weight--it looks like a template/outline. This makes sense because the prediction is the inner product of the input and weights, and therefore if one wants a higher weight in a certain category, the weight should be close to a sample image (though not too close--beware overfitting).*

---

2 IMPORTANT

This is the end of this question. Please do the following:

1. Click `File -> Save` to make sure the latest checkpoint of this notebook is saved to your Drive.

2. Execute the cell below to download the modified .py files back to your drive.

[0]:
```
import os

FOLDER_TO_SAVE = os.path.join('drive/My Drive/', FOLDERNAME)
FILES_TO_SAVE = ['cs231n/classifiers/linear_svm.py', 'cs231n/classifiers/
 ↪linear_classifier.py']

for files in FILES_TO_SAVE:
  with open(os.path.join(FOLDER_TO_SAVE, '/'.join(files.split('/')[1:])), 'w')␣
 ↪as f:
    f.write(''.join(open(files).readlines()))
```

softmax

April 20, 2020

[1]:
```
from google.colab import drive

drive.mount('/content/drive', force_remount=True)

# enter the foldername in your Drive where you have saved the unzipped
# 'cs231n' folder containing the '.py', 'classifiers' and 'datasets'
# folders.
# e.g. 'cs231n/assignments/assignment1/cs231n/'
FOLDERNAME = 'CS231N/assignment1/cs231n/'

assert FOLDERNAME is not None, "[!] Enter the foldername."

%cd drive/My\ Drive
%cp -r $FOLDERNAME ../../
%cd ../../
%cd cs231n/datasets/
!bash get_datasets.sh
%cd ../../
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id
=947318989803-6bn6qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleusercontent.com&redire
ct_uri=urn%3aietf%3awg%3aoauth%3a2.0%3aoob&response_type=code&scope=email%20http
s%3a%2f%2fwww.googleapis.com%2fauth%2fdocs.test%20https%3a%2f%2fwww.googleapis.c
om%2fauth%2fdrive%20https%3a%2f%2fwww.googleapis.com%2fauth%2fdrive.photos.reado
nly%20https%3a%2f%2fwww.googleapis.com%2fauth%2fpeopleapi.readonly

Enter your authorization code:
ůůůůůůůůůů
Mounted at /content/drive
/content/drive/My Drive
/content
/content/cs231n/datasets
--2020-04-20 04:08:38--  http://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
Resolving www.cs.toronto.edu (www.cs.toronto.edu)... 128.100.3.30
Connecting to www.cs.toronto.edu (www.cs.toronto.edu)|128.100.3.30|:80...
connected.
HTTP request sent, awaiting response... 200 OK
```

```
Length: 170498071 (163M) [application/x-gzip]
Saving to: cifar-10-python.tar.gz

cifar-10-python.tar 100%[===================>] 162.60M  47.2MB/s    in 3.8s

2020-04-20 04:08:42 (43.2 MB/s) - cifar-10-python.tar.gz saved
[170498071/170498071]

cifar-10-batches-py/
cifar-10-batches-py/data_batch_4
cifar-10-batches-py/readme.html
cifar-10-batches-py/test_batch
cifar-10-batches-py/data_batch_3
cifar-10-batches-py/batches.meta
cifar-10-batches-py/data_batch_2
cifar-10-batches-py/data_batch_5
cifar-10-batches-py/data_batch_1
/content
```

1 Softmax exercise

Complete and hand in this completed worksheet (including its outputs and any supporting code outside of the worksheet) with your assignment submission. For more details see the assignments page on the course website.

This exercise is analogous to the SVM exercise. You will:

- implement a fully-vectorized **loss function** for the Softmax classifier
- implement the fully-vectorized expression for its **analytic gradient**
- **check your implementation** with numerical gradient
- use a validation set to **tune the learning rate and regularization** strength
- **optimize** the loss function with **SGD**
- **visualize** the final learned weights

[0]:
```
import random
import numpy as np
from cs231n.data_utils import load_CIFAR10
import matplotlib.pyplot as plt

%matplotlib inline
plt.rcParams['figure.figsize'] = (10.0, 8.0) # set default size of plots
plt.rcParams['image.interpolation'] = 'nearest'
plt.rcParams['image.cmap'] = 'gray'

# for auto-reloading extenrnal modules
# see http://stackoverflow.com/questions/1907993/
 ↪autoreload-of-modules-in-ipython
%load_ext autoreload
```

```
%autoreload 2
```

[3]:
```
def get_CIFAR10_data(num_training=49000, num_validation=1000, num_test=1000,␣
↪num_dev=500):
    """
    Load the CIFAR-10 dataset from disk and perform preprocessing to prepare
    it for the linear classifier. These are the same steps as we used for the
    SVM, but condensed to a single function.
    """
    # Load the raw CIFAR-10 data
    cifar10_dir = 'cs231n/datasets/cifar-10-batches-py'

    # Cleaning up variables to prevent loading data multiple times (which may␣
↪cause memory issue)
    try:
       del X_train, y_train
       del X_test, y_test
       print('Clear previously loaded data.')
    except:
       pass

    X_train, y_train, X_test, y_test = load_CIFAR10(cifar10_dir)

    # subsample the data
    mask = list(range(num_training, num_training + num_validation))
    X_val = X_train[mask]
    y_val = y_train[mask]
    mask = list(range(num_training))
    X_train = X_train[mask]
    y_train = y_train[mask]
    mask = list(range(num_test))
    X_test = X_test[mask]
    y_test = y_test[mask]
    mask = np.random.choice(num_training, num_dev, replace=False)
    X_dev = X_train[mask]
    y_dev = y_train[mask]

    # Preprocessing: reshape the image data into rows
    X_train = np.reshape(X_train, (X_train.shape[0], -1))
    X_val = np.reshape(X_val, (X_val.shape[0], -1))
    X_test = np.reshape(X_test, (X_test.shape[0], -1))
    X_dev = np.reshape(X_dev, (X_dev.shape[0], -1))

    # Normalize the data: subtract the mean image
    mean_image = np.mean(X_train, axis = 0)
    X_train -= mean_image
    X_val -= mean_image
```

```
    X_test -= mean_image
    X_dev -= mean_image

    # add bias dimension and transform into columns
    X_train = np.hstack([X_train, np.ones((X_train.shape[0], 1))])
    X_val = np.hstack([X_val, np.ones((X_val.shape[0], 1))])
    X_test = np.hstack([X_test, np.ones((X_test.shape[0], 1))])
    X_dev = np.hstack([X_dev, np.ones((X_dev.shape[0], 1))])

    return X_train, y_train, X_val, y_val, X_test, y_test, X_dev, y_dev


# Invoke the above function to get our data.
X_train, y_train, X_val, y_val, X_test, y_test, X_dev, y_dev =␣
 ↪get_CIFAR10_data()
print('Train data shape: ', X_train.shape)
print('Train labels shape: ', y_train.shape)
print('Validation data shape: ', X_val.shape)
print('Validation labels shape: ', y_val.shape)
print('Test data shape: ', X_test.shape)
print('Test labels shape: ', y_test.shape)
print('dev data shape: ', X_dev.shape)
print('dev labels shape: ', y_dev.shape)
```

```
Train data shape:  (49000, 3073)
Train labels shape:  (49000,)
Validation data shape:  (1000, 3073)
Validation labels shape:  (1000,)
Test data shape:  (1000, 3073)
Test labels shape:  (1000,)
dev data shape:  (500, 3073)
dev labels shape:  (500,)
```

1.1 Softmax Classifier

Your code for this section will all be written inside `cs231n/classifiers/softmax.py`.

[4]:
```
# First implement the naive softmax loss function with nested loops.
# Open the file cs231n/classifiers/softmax.py and implement the
# softmax_loss_naive function.

from cs231n.classifiers.softmax import softmax_loss_naive
import time

# Generate a random softmax weight matrix and use it to compute the loss.
W = np.random.randn(3073, 10) * 0.0001
loss, grad = softmax_loss_naive(W, X_dev, y_dev, 0.0)
```

```
# As a rough sanity check, our loss should be something close to -log(0.1).
print('loss: %f' % loss)
print('sanity check: %f' % (-np.log(0.1)))
```

```
loss: 2.363021
sanity check: 2.302585
```

Inline Question 1

Why do we expect our loss to be close to -log(0.1)? Explain briefly.**

Your Answer : *We know that W is randomly assigned according to a uniform distribution; as such, we know that the probability of any category being assigned is* $\frac{1}{10}$. *We can therefore see that the cross-entropy between our true and estimated distributions is 0.1, and our resulting log loss is* $-\log(0.1)$.

[5]:
```
# Complete the implementation of softmax_loss_naive and implement a (naive)
# version of the gradient that uses nested loops.
loss, grad = softmax_loss_naive(W, X_dev, y_dev, 0.0)

# As we did for the SVM, use numeric gradient checking as a debugging tool.
# The numeric gradient should be close to the analytic gradient.
from cs231n.gradient_check import grad_check_sparse
f = lambda w: softmax_loss_naive(w, X_dev, y_dev, 0.0)[0]
grad_numerical = grad_check_sparse(f, W, grad, 10)

# similar to SVM case, do another gradient check with regularization
loss, grad = softmax_loss_naive(W, X_dev, y_dev, 5e1)
f = lambda w: softmax_loss_naive(w, X_dev, y_dev, 5e1)[0]
grad_numerical = grad_check_sparse(f, W, grad, 10)
```

```
numerical: -0.286841 analytic: -0.286841, relative error: 1.784724e-07
numerical: -1.635496 analytic: -1.635496, relative error: 1.756058e-08
numerical: -0.096975 analytic: -0.096975, relative error: 3.178494e-07
numerical: -0.470773 analytic: -0.470773, relative error: 4.027507e-08
numerical: 3.384561 analytic: 3.384561, relative error: 2.352719e-08
numerical: -0.133106 analytic: -0.133105, relative error: 2.591155e-07
numerical: -0.706238 analytic: -0.706238, relative error: 1.862879e-08
numerical: -0.172551 analytic: -0.172551, relative error: 4.466372e-07
numerical: -0.184198 analytic: -0.184198, relative error: 3.777108e-07
numerical: 0.639550 analytic: 0.639550, relative error: 5.513507e-08
numerical: 5.891644 analytic: 5.891644, relative error: 3.064460e-09
numerical: 0.351477 analytic: 0.351477, relative error: 1.602577e-07
numerical: 0.298043 analytic: 0.298043, relative error: 8.792528e-09
numerical: 0.466010 analytic: 0.466010, relative error: 6.155663e-08
numerical: -1.244690 analytic: -1.244690, relative error: 6.817652e-08
numerical: -2.180200 analytic: -2.180200, relative error: 1.002329e-09
numerical: -1.035983 analytic: -1.035983, relative error: 2.527413e-08
numerical: 1.051160 analytic: 1.051160, relative error: 5.607428e-08
numerical: 1.420065 analytic: 1.420065, relative error: 3.504127e-08
numerical: 1.088438 analytic: 1.088438, relative error: 5.993882e-09
```

[6]:
```
# Now that we have a naive implementation of the softmax loss function and its␣
↪gradient,
# implement a vectorized version in softmax_loss_vectorized.
# The two versions should compute the same results, but the vectorized version␣
↪should be
# much faster.
tic = time.time()
loss_naive, grad_naive = softmax_loss_naive(W, X_dev, y_dev, 0.000005)
toc = time.time()
print('naive loss: %e computed in %fs' % (loss_naive, toc - tic))

from cs231n.classifiers.softmax import softmax_loss_vectorized
tic = time.time()
loss_vectorized, grad_vectorized = softmax_loss_vectorized(W, X_dev, y_dev, 0.
↪000005)
toc = time.time()
print('vectorized loss: %e computed in %fs' % (loss_vectorized, toc - tic))

# As we did for the SVM, we use the Frobenius norm to compare the two versions
# of the gradient.
grad_difference = np.linalg.norm(grad_naive - grad_vectorized, ord='fro')
print('Loss difference: %f' % np.abs(loss_naive - loss_vectorized))
print('Gradient difference: %f' % grad_difference)
```

```
naive loss: 2.363021e+00 computed in 0.208777s
vectorized loss: 2.363021e+00 computed in 0.019506s
Loss difference: 0.000000
Gradient difference: 0.000000
```

[7]:
```
# Use the validation set to tune hyperparameters (regularization strength and
# learning rate). You should experiment with different ranges for the learning
# rates and regularization strengths; if you are careful you should be able to
# get a classification accuracy of over 0.35 on the validation set.

from cs231n.classifiers import Softmax
results = {}
best_val = -1
best_softmax = None

################################################################################
# TODO:                                                                        ␣
↪#
# Use the validation set to set the learning rate and regularization strength.␣
↪#
# This should be identical to the validation that you did for the SVM; save   ␣
↪#
```

```
# the best trained softmax classifer in best_softmax.                          ␣
↪#
################################################################################

# Provided as a reference. You may or may not want to change these␣
↪hyperparameters
learning_rates = [4.4e-7, 4.5e-7, 4.6e-7]
regularization_strengths = [2.5e4, 2.6e4, 2.7e4, 2.8e4, 2.9e4]

# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
num_val = X_val.shape[0]
d = X_val.shape[1]

for l in learning_rates:
  for r in regularization_strengths:
    sm = Softmax()
    loss_hist = sm.train(X_train, y_train, l, r, num_iters=2000)
    y_train_pred = sm.predict(X_train)
    y_val_pred = sm.predict(X_val)
    train_accuracy = np.mean(y_train_pred == y_train)
    val_accuracy = np.mean(y_val_pred == y_val)
    results[(l, r)] = train_accuracy, val_accuracy
    if val_accuracy > best_val:
            best_val = val_accuracy
            best_softmax = sm

# *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

# Print out results.
for lr, reg in sorted(results):
    train_accuracy, val_accuracy = results[(lr, reg)]
    print('lr %e reg %e train accuracy: %f val accuracy: %f' % (
                lr, reg, train_accuracy, val_accuracy))

print('best validation accuracy achieved during cross-validation: %f' %␣
↪best_val)
```

```
lr 4.400000e-07 reg 2.500000e+04 train accuracy: 0.350714 val accuracy: 0.364000
lr 4.400000e-07 reg 2.600000e+04 train accuracy: 0.337490 val accuracy: 0.365000
lr 4.400000e-07 reg 2.700000e+04 train accuracy: 0.350306 val accuracy: 0.360000
lr 4.400000e-07 reg 2.800000e+04 train accuracy: 0.347388 val accuracy: 0.359000
lr 4.400000e-07 reg 2.900000e+04 train accuracy: 0.339980 val accuracy: 0.357000
lr 4.500000e-07 reg 2.500000e+04 train accuracy: 0.349980 val accuracy: 0.362000
lr 4.500000e-07 reg 2.600000e+04 train accuracy: 0.353796 val accuracy: 0.368000
lr 4.500000e-07 reg 2.700000e+04 train accuracy: 0.343980 val accuracy: 0.347000
lr 4.500000e-07 reg 2.800000e+04 train accuracy: 0.334082 val accuracy: 0.350000
lr 4.500000e-07 reg 2.900000e+04 train accuracy: 0.338490 val accuracy: 0.363000
```

```
lr 4.600000e-07 reg 2.500000e+04 train accuracy: 0.346143 val accuracy: 0.359000
lr 4.600000e-07 reg 2.600000e+04 train accuracy: 0.346959 val accuracy: 0.362000
lr 4.600000e-07 reg 2.700000e+04 train accuracy: 0.344306 val accuracy: 0.369000
lr 4.600000e-07 reg 2.800000e+04 train accuracy: 0.344592 val accuracy: 0.358000
lr 4.600000e-07 reg 2.900000e+04 train accuracy: 0.341633 val accuracy: 0.362000
best validation accuracy achieved during cross-validation: 0.369000
```

[8]:
```
# evaluate on test set
# Evaluate the best softmax on test set
y_test_pred = best_softmax.predict(X_test)
test_accuracy = np.mean(y_test == y_test_pred)
print('softmax on raw pixels final test set accuracy: %f' % (test_accuracy, ))
```

```
softmax on raw pixels final test set accuracy: 0.349000
```

Inline Question 2 - *True or False*

Suppose the overall training loss is defined as the sum of the per-datapoint loss over all training examples. It is possible to add a new datapoint to a training set that would leave the SVM loss unchanged, but this is not the case with the Softmax classifier loss.

$Your Answer$: True

$Your Explanation$: To understand this result, let is us consider the individual loss of the added datapoint. For softmax, we can see that adding this datapoint will affect the loss function regardless of the correctness of the classification. This is because the cross-entropy loss function takes into account the scores of all other categories $j\ \forall j \neq y_i$. However, the SVM loss function is considered a local objective: as long as the datapoint is correctly classified such that the difference in scores between the the correct category and first runner-up is greater than the margin, then nothing is added to the loss as $\max(0, s_j - s_{y_i} + \Delta) = 0\ \ \forall j$. Because with every data point, a non-zero loss is added to the cross-entropy cost function, but no loss may be added to SVM cost function, the statement above is possible.

[9]:
```
# Visualize the learned weights for each class
w = best_softmax.W[:-1,:] # strip out the bias
w = w.reshape(32, 32, 3, 10)

w_min, w_max = np.min(w), np.max(w)

classes = ['plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse',␣
 ↪'ship', 'truck']
for i in range(10):
    plt.subplot(2, 5, i + 1)

    # Rescale the weights to be between 0 and 255
    wimg = 255.0 * (w[:, :, :, i].squeeze() - w_min) / (w_max - w_min)
    plt.imshow(wimg.astype('uint8'))
    plt.axis('off')
    plt.title(classes[i])
```

---

2 IMPORTANT

This is the end of this question. Please do the following:

1. Click `File -> Save` to make sure the latest checkpoint of this notebook is saved to your Drive.
2. Execute the cell below to download the modified `.py` files back to your drive.

[0]:
```
import os

FOLDER_TO_SAVE = os.path.join('drive/My Drive/', FOLDERNAME)
FILES_TO_SAVE = ['cs231n/classifiers/softmax.py']

for files in FILES_TO_SAVE:
  with open(os.path.join(FOLDER_TO_SAVE, '/'.join(files.split('/')[1:])), 'w') as f:
    f.write(''.join(open(files).readlines()))
```

two_layer_net

April 20, 2020

[1]:
```
from google.colab import drive

drive.mount('/content/drive', force_remount=True)

# enter the foldername in your Drive where you have saved the unzipped
# 'cs231n' folder containing the '.py', 'classifiers' and 'datasets'
# folders.
# e.g. 'cs231n/assignments/assignment1/cs231n/'
FOLDERNAME = 'CS231N/assignment1/cs231n'

assert FOLDERNAME is not None, "[!] Enter the foldername."

%cd drive/My\ Drive
%cp -r $FOLDERNAME ../../
%cd ../../
%cd cs231n/datasets/
!bash get_datasets.sh
%cd ../../
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id
=947318989803-6bn6qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleusercontent.com&redire
ct_uri=urn%3aietf%3awg%3aoauth%3a2.0%3aoob&response_type=code&scope=email%20http
s%3a%2f%2fwww.googleapis.com%2fauth%2fdocs.test%20https%3a%2f%2fwww.googleapis.c
om%2fauth%2fdrive%20https%3a%2f%2fwww.googleapis.com%2fauth%2fdrive.photos.reado
nly%20https%3a%2f%2fwww.googleapis.com%2fauth%2fpeopleapi.readonly

Enter your authorization code:
ůůůůůůůůůů
Mounted at /content/drive
/content/drive/My Drive
/content
/content/cs231n/datasets
--2020-04-18 01:34:09--  http://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
Resolving www.cs.toronto.edu (www.cs.toronto.edu)... 128.100.3.30
Connecting to www.cs.toronto.edu (www.cs.toronto.edu)|128.100.3.30|:80...
connected.
```

```
HTTP request sent, awaiting response... 200 OK
Length: 170498071 (163M) [application/x-gzip]
Saving to: cifar-10-python.tar.gz

cifar-10-python.tar 100%[===================>] 162.60M  33.3MB/s    in 5.3s

2020-04-18 01:34:15 (30.6 MB/s) - cifar-10-python.tar.gz saved
[170498071/170498071]

cifar-10-batches-py/
cifar-10-batches-py/data_batch_4
cifar-10-batches-py/readme.html
cifar-10-batches-py/test_batch
cifar-10-batches-py/data_batch_3
cifar-10-batches-py/batches.meta
cifar-10-batches-py/data_batch_2
cifar-10-batches-py/data_batch_5
cifar-10-batches-py/data_batch_1
/content
```

1 Implementing a Neural Network

In this exercise we will develop a neural network with fully-connected layers to perform classification, and test it out on the CIFAR-10 dataset.

[0]:
```
# A bit of setup

import numpy as np
import matplotlib.pyplot as plt

from cs231n.classifiers.neural_net import TwoLayerNet

%matplotlib inline
plt.rcParams['figure.figsize'] = (10.0, 8.0) # set default size of plots
plt.rcParams['image.interpolation'] = 'nearest'
plt.rcParams['image.cmap'] = 'gray'

# for auto-reloading external modules
# see http://stackoverflow.com/questions/1907993/
 ↪autoreload-of-modules-in-ipython
%load_ext autoreload
%autoreload 2

def rel_error(x, y):
    """ returns relative error """
    return np.max(np.abs(x - y) / (np.maximum(1e-8, np.abs(x) + np.abs(y))))
```

We will use the class `TwoLayerNet` in the file `cs231n/classifiers/neural_net.py` to represent instances of our network. The network parameters are stored in the instance variable `self.params` where keys are string parameter names and values are numpy arrays. Below, we initialize toy data and a toy model that we will use to develop your implementation.

[0]:
```
# Create a small net and some toy data to check your implementations.
# Note that we set the random seed for repeatable experiments.

input_size = 4
hidden_size = 10
num_classes = 3
num_inputs = 5

def init_toy_model():
    np.random.seed(0)
    return TwoLayerNet(input_size, hidden_size, num_classes, std=1e-1)

def init_toy_data():
    np.random.seed(1)
    X = 10 * np.random.randn(num_inputs, input_size)
    y = np.array([0, 1, 2, 2, 1])
    return X, y

net = init_toy_model()
X, y = init_toy_data()
```

2 Forward pass: compute scores

Open the file `cs231n/classifiers/neural_net.py` and look at the method `TwoLayerNet.loss`. This function is very similar to the loss functions you have written for the SVM and Softmax exercises: It takes the data and weights and computes the class scores, the loss, and the gradients on the parameters.

Implement the first part of the forward pass which uses the weights and biases to compute the scores for all inputs.

[4]:
```
scores = net.loss(X)
print('Your scores:')
print(scores)
print()
print('correct scores:')
correct_scores = np.asarray([
  [-0.81233741, -1.27654624, -0.70335995],
  [-0.17129677, -1.18803311, -0.47310444],
  [-0.51590475, -1.01354314, -0.8504215 ],
  [-0.15419291, -0.48629638, -0.52901952],
  [-0.00618733, -0.12435261, -0.15226949]])
print(correct_scores)
print()
```

```
# The difference should be very small. We get < 1e-7
print('Difference between your scores and correct scores:')
print(np.sum(np.abs(scores - correct_scores)))
```

```
Your scores:
[[-0.81233741 -1.27654624 -0.70335995]
 [-0.17129677 -1.18803311 -0.47310444]
 [-0.51590475 -1.01354314 -0.8504215 ]
 [-0.15419291 -0.48629638 -0.52901952]
 [-0.00618733 -0.12435261 -0.15226949]]

correct scores:
[[-0.81233741 -1.27654624 -0.70335995]
 [-0.17129677 -1.18803311 -0.47310444]
 [-0.51590475 -1.01354314 -0.8504215 ]
 [-0.15419291 -0.48629638 -0.52901952]
 [-0.00618733 -0.12435261 -0.15226949]]

Difference between your scores and correct scores:
3.6802720745909845e-08
```

3 Forward pass: compute loss

In the same function, implement the second part that computes the data and regularization loss.

[7]:
```
loss, _ = net.loss(X, y, reg=0.05)
correct_loss = 1.30378789133

# should be very small, we get < 1e-12
print('Difference between your loss and correct loss:')
print(np.sum(np.abs(loss - correct_loss)))
```

```
Difference between your loss and correct loss:
1.794120407794253e-13
```

4 Backward pass

Implement the rest of the function. This will compute the gradient of the loss with respect to the variables `W1`, `b1`, `W2`, and `b2`. Now that you (hopefully!) have a correctly implemented forward pass, you can debug your backward pass using a numeric gradient check:

[8]:
```
from cs231n.gradient_check import eval_numerical_gradient

# Use numeric gradient checking to check your implementation of the backward␣
↪pass.
# If your implementation is correct, the difference between the numeric and
# analytic gradients should be less than 1e-8 for each of W1, W2, b1, and b2.
```

```
loss, grads = net.loss(X, y, reg=0.05)

# these should all be less than 1e-8 or so
for param_name in grads:
    f = lambda W: net.loss(X, y, reg=0.05)[0]
    param_grad_num = eval_numerical_gradient(f, net.params[param_name],␣
 ↪verbose=False)
    print('%s max relative error: %e' % (param_name, rel_error(param_grad_num,␣
 ↪grads[param_name])))
```

```
W1 max relative error: 3.561318e-09
W2 max relative error: 3.440708e-09
b1 max relative error: 2.738421e-09
b2 max relative error: 4.447625e-11
```

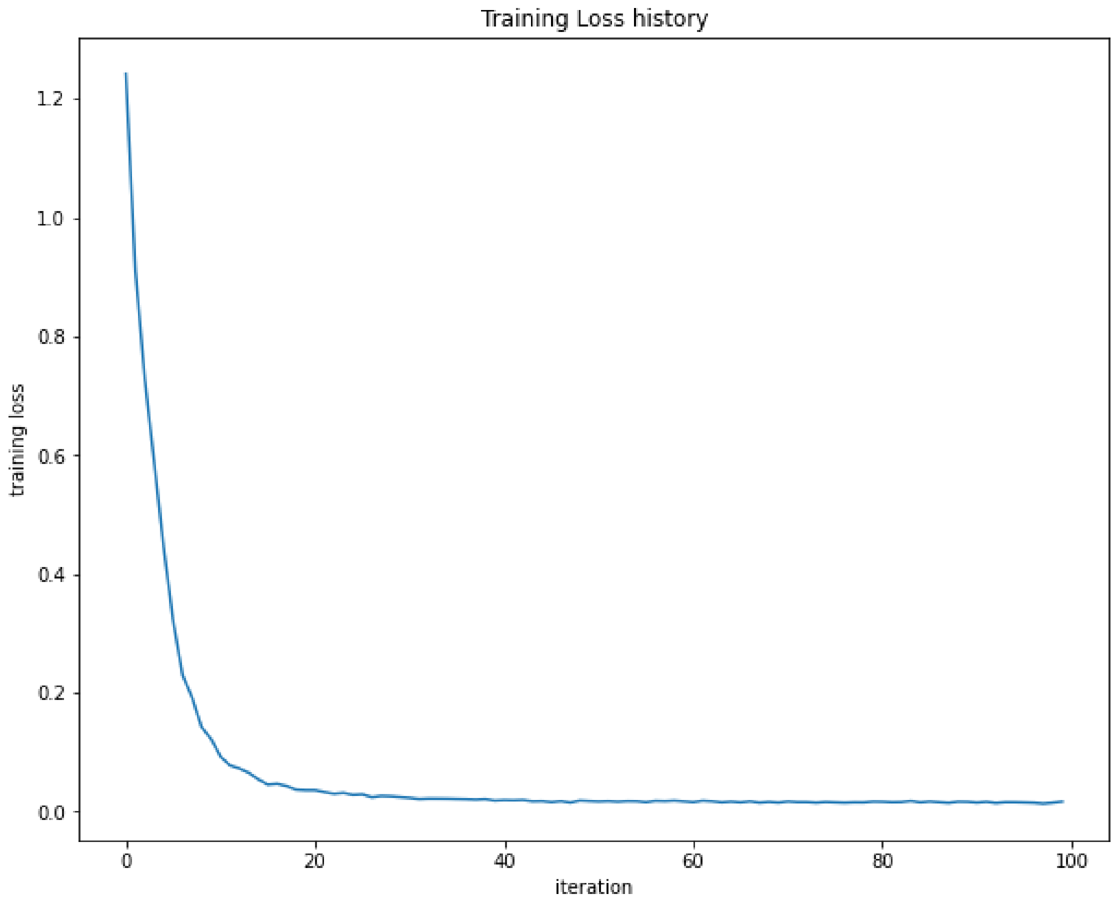
5 Train the network

To train the network we will use stochastic gradient descent (SGD), similar to the SVM and Softmax classifiers. Look at the function `TwoLayerNet.train` and fill in the missing sections to implement the training procedure. This should be very similar to the training procedure you used for the SVM and Softmax classifiers. You will also have to implement `TwoLayerNet.predict`, as the training process periodically performs prediction to keep track of accuracy over time while the network trains.

Once you have implemented the method, run the code below to train a two-layer network on toy data. You should achieve a training loss less than 0.02.

[9]:
```
net = init_toy_model()
stats = net.train(X, y, X, y,
            learning_rate=1e-1, reg=5e-6,
            num_iters=100, verbose=False)

print('Final training loss: ', stats['loss_history'][-1])

# plot the loss history
plt.plot(stats['loss_history'])
plt.xlabel('iteration')
plt.ylabel('training loss')
plt.title('Training Loss history')
plt.show()
```

```
Final training loss:  0.017149607938732093
```



6 Load the data

Now that you have implemented a two-layer network that passes gradient checks and works on toy data, it's time to load up our favorite CIFAR-10 data so we can use it to train a classifier on a real dataset.

[10]:
```
from cs231n.data_utils import load_CIFAR10

def get_CIFAR10_data(num_training=49000, num_validation=1000, num_test=1000):
    """
    Load the CIFAR-10 dataset from disk and perform preprocessing to prepare
    it for the two-layer neural net classifier. These are the same steps as
    we used for the SVM, but condensed to a single function.
    """
    # Load the raw CIFAR-10 data
    cifar10_dir = 'cs231n/datasets/cifar-10-batches-py'

    # Cleaning up variables to prevent loading data multiple times (which may␣
 ↪cause memory issue)
```

```
    try:
        del X_train, y_train
        del X_test, y_test
        print('Clear previously loaded data.')
    except:
        pass

    X_train, y_train, X_test, y_test = load_CIFAR10(cifar10_dir)

    # Subsample the data
    mask = list(range(num_training, num_training + num_validation))
    X_val = X_train[mask]
    y_val = y_train[mask]
    mask = list(range(num_training))
    X_train = X_train[mask]
    y_train = y_train[mask]
    mask = list(range(num_test))
    X_test = X_test[mask]
    y_test = y_test[mask]

    # Normalize the data: subtract the mean image
    mean_image = np.mean(X_train, axis=0)
    X_train -= mean_image
    X_val -= mean_image
    X_test -= mean_image

    # Reshape data to rows
    X_train = X_train.reshape(num_training, -1)
    X_val = X_val.reshape(num_validation, -1)
    X_test = X_test.reshape(num_test, -1)

    return X_train, y_train, X_val, y_val, X_test, y_test


# Invoke the above function to get our data.
X_train, y_train, X_val, y_val, X_test, y_test = get_CIFAR10_data()
print('Train data shape: ', X_train.shape)
print('Train labels shape: ', y_train.shape)
print('Validation data shape: ', X_val.shape)
print('Validation labels shape: ', y_val.shape)
print('Test data shape: ', X_test.shape)
print('Test labels shape: ', y_test.shape)
```

```
Train data shape:  (49000, 3072)
Train labels shape:  (49000,)
Validation data shape:  (1000, 3072)
Validation labels shape:  (1000,)
```

```
Test data shape:  (1000, 3072)
Test labels shape:  (1000,)
```

7 Train a network

To train our network we will use SGD. In addition, we will adjust the learning rate with an exponential learning rate schedule as optimization proceeds; after each epoch, we will reduce the learning rate by multiplying it by a decay rate.

[11]:
```python
input_size = 32 * 32 * 3
hidden_size = 50
num_classes = 10
net = TwoLayerNet(input_size, hidden_size, num_classes)

# Train the network
stats = net.train(X_train, y_train, X_val, y_val,
            num_iters=1000, batch_size=200,
            learning_rate=1e-4, learning_rate_decay=0.95,
            reg=0.25, verbose=True)

# Predict on the validation set
val_acc = (net.predict(X_val) == y_val).mean()
print('Validation accuracy: ', val_acc)
```

```
iteration 0 / 1000: loss 2.302954
iteration 100 / 1000: loss 2.302550
iteration 200 / 1000: loss 2.297648
iteration 300 / 1000: loss 2.259602
iteration 400 / 1000: loss 2.204170
iteration 500 / 1000: loss 2.118565
iteration 600 / 1000: loss 2.051535
iteration 700 / 1000: loss 1.988466
iteration 800 / 1000: loss 2.006591
iteration 900 / 1000: loss 1.951473
Validation accuracy:  0.287
```

8 Debug the training

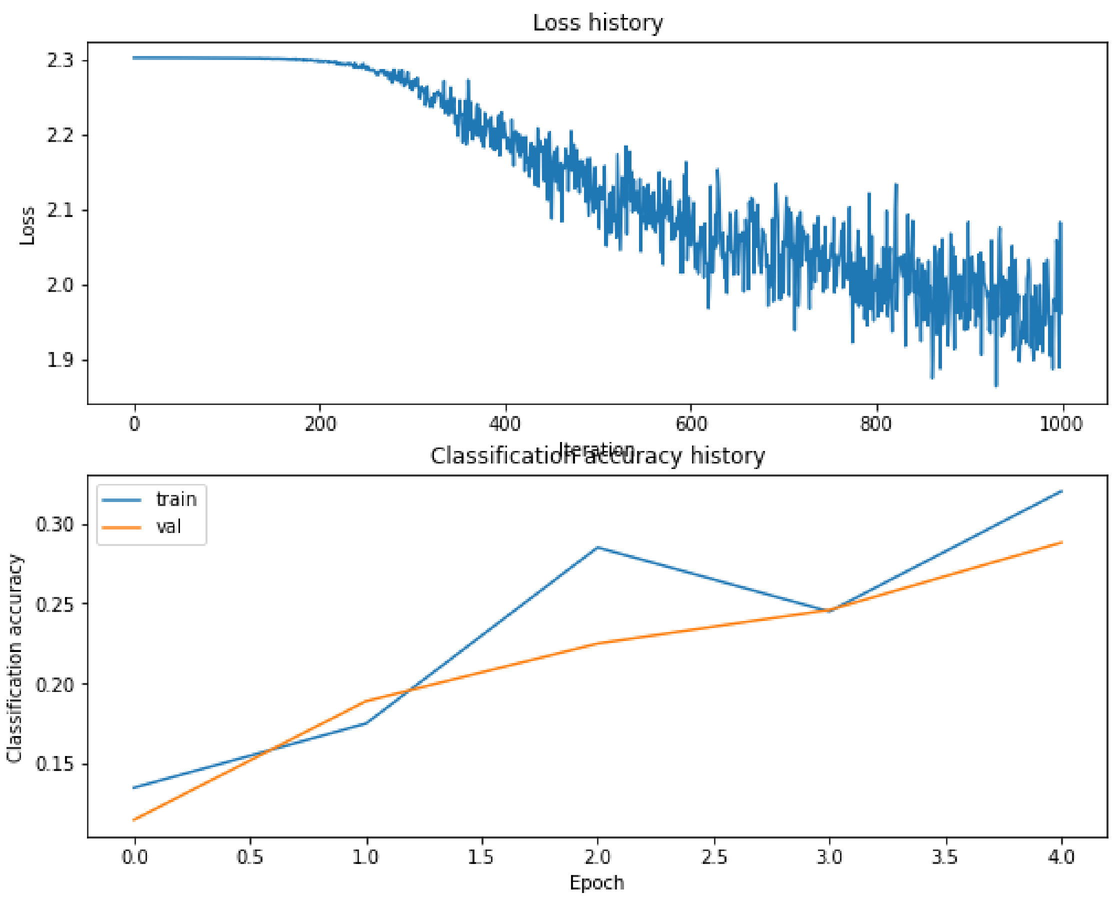
With the default parameters we provided above, you should get a validation accuracy of about 0.29 on the validation set. This isn't very good.

One strategy for getting insight into what's wrong is to plot the loss function and the accuracies on the training and validation sets during optimization.

Another strategy is to visualize the weights that were learned in the first layer of the network. In most neural networks trained on visual data, the first layer weights typically show some visible structure when visualized.

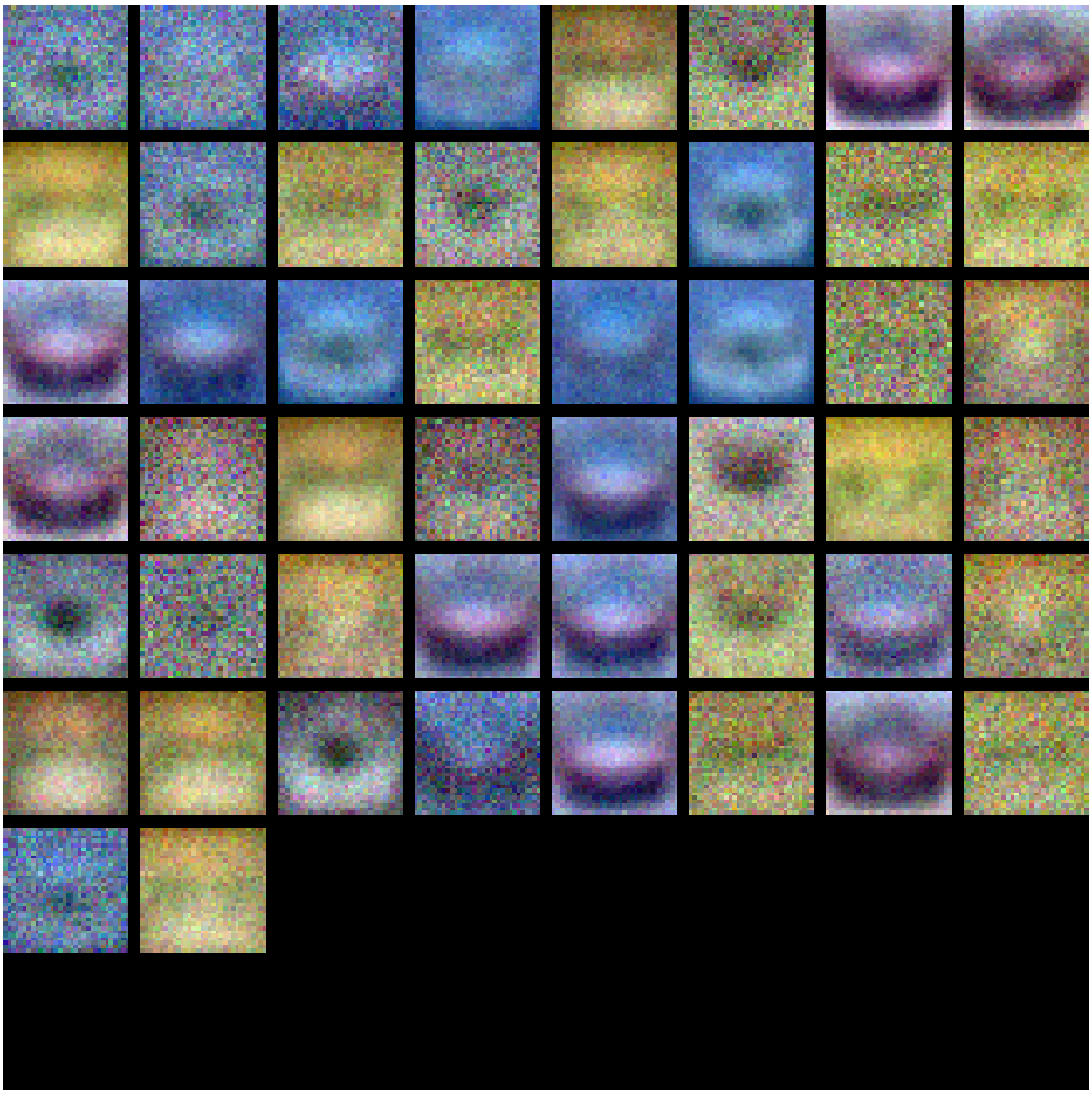
[12]:
```python
# Plot the loss function and train / validation accuracies
plt.subplot(2, 1, 1)
```

```
plt.plot(stats['loss_history'])
plt.title('Loss history')
plt.xlabel('Iteration')
plt.ylabel('Loss')

plt.subplot(2, 1, 2)
plt.plot(stats['train_acc_history'], label='train')
plt.plot(stats['val_acc_history'], label='val')
plt.title('Classification accuracy history')
plt.xlabel('Epoch')
plt.ylabel('Classification accuracy')
plt.legend()
plt.show()
```



[13]:
```
from cs231n.vis_utils import visualize_grid

# Visualize the weights of the network

def show_net_weights(net):
```

```
    W1 = net.params['W1']
    W1 = W1.reshape(32, 32, 3, -1).transpose(3, 0, 1, 2)
    plt.imshow(visualize_grid(W1, padding=3).astype('uint8'))
    plt.gca().axis('off')
    plt.show()

show_net_weights(net)
```



9 Tune your hyperparameters

What's wrong?. Looking at the visualizations above, we see that the loss is decreasing more or less linearly, which seems to suggest that the learning rate may be too low. Moreover, there is no gap between the training and validation accuracy, suggesting that the model we used has low capacity, and that we should increase its size. On the other hand, with a very large model we would expect to see more overfitting, which would manifest itself as a very large gap between the training and validation accuracy.

Tuning. Tuning the hyperparameters and developing intuition for how they affect the final performance is a large part of using Neural Networks, so we want you to get a lot of practice. Below, you should experiment with different values of the various hyperparameters, including hidden layer size, learning rate, numer of training epochs, and regularization strength. You might also consider tuning the learning rate decay, but you should be able to get good performance using the default value.

Approximate results. You should be aim to achieve a classification accuracy of greater than 48% on the validation set. Our best network gets over 52% on the validation set.

Experiment: You goal in this exercise is to get as good of a result on CIFAR-10 as you can (52% could serve as a reference), with a fully-connected Neural Network. Feel free implement your own techniques (e.g. PCA to reduce dimensionality, or adding dropout, or adding features to the solver, etc.).

Explain your hyperparameter tuning process below.

Your Answer : There were three metrics tuned: hidden layer size, learning rate, and regularization strength. I first isolated the hidden layer size, testing values from 100-500. It is known that two-layer neural nets can perform more like deep nets if they have exponentially more neurons in the hidden layer. So any ties were broken by choosing the higher number of neurons.

Second, I tuned the regularization strengths by experimenting with values from 1e-4 to 1. Condensing the three values to 0.9e-2 to 1.1e-2, it was clear that one performed the best for learning rates between 1e-2 and 2e-2.

Lastly, I tuned learning rate, though while tuning the reg strength I had isolated the range of the learning rate to 1.4e-3 to 1.7e-3. Some values above 3 performed equally well, but would not return the same results as consistently. Because I wanted to raise the number of iterations but maintain total runtime of the cell, I then settled on 1-2 numbers for each hyperparamater. After raising the num_iters by 12.5x, the results converged to a much better value than expected.

[14]:
```
best_net = None # store the best model into this

################################################################################
# TODO: Tune hyperparameters using the validation set. Store your best trained ␣
↪#
# model in best_net.                                                           ␣
↪#
#                                                                              ␣
↪#
# To help debug your network, it may help to use visualizations similar to the ␣
↪#
# ones we used above; these visualizations will have significant qualitative   ␣
↪#
# differences from the ones we saw above for the poorly tuned network.         ␣
↪#
#                                                                              ␣
↪#
```

```
# Tweaking hyperparameters by hand can be fun, but you might find it useful to␣
↪#
# write code to sweep through possible combinations of hyperparameters          ␣
↪#
# automatically like we did on the previous exercises.                          ␣
↪#
#################################################################################
# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
input_size = 32 * 32 * 3
num_classes = 10

results = {}
best_val = 0.0

hidden_size = [400, 428]
learning_rates = [1.6e-3]
regularization_strengths = [1e-2]


for h in hidden_size:
    for l in learning_rates:
        for r in regularization_strengths:
          nn = TwoLayerNet(input_size, h, num_classes)
          nn.train(X_train, y_train, X_val, y_val, learning_rate=l, reg=r,␣
↪num_iters=2500)
          y_train_pred = nn.predict(X_train)
          y_val_pred = nn.predict(X_val)
          train_accuracy = np.mean(y_train_pred == y_train)
          val_accuracy = np.mean(y_val_pred == y_val)
          results[(h, l, r)] = train_accuracy, val_accuracy
          print('hidden_size %f learn_rate %e reg_str %e train accuracy: %f val␣
↪accuracy: %f' % (h,
                l, r, train_accuracy, val_accuracy))

          if val_accuracy > best_val:
              best_val = val_accuracy
              best_net = nn

# Print out results.
# for h, l, r in sorted(results):
#     train_accuracy, val_accuracy = results[(h, l, r)]
#     print('hidden_size %f learn_rate %e reg_str %e train accuracy: %f val␣
↪accuracy: %f' % (h,
#                 l, r, train_accuracy, val_accuracy))
```

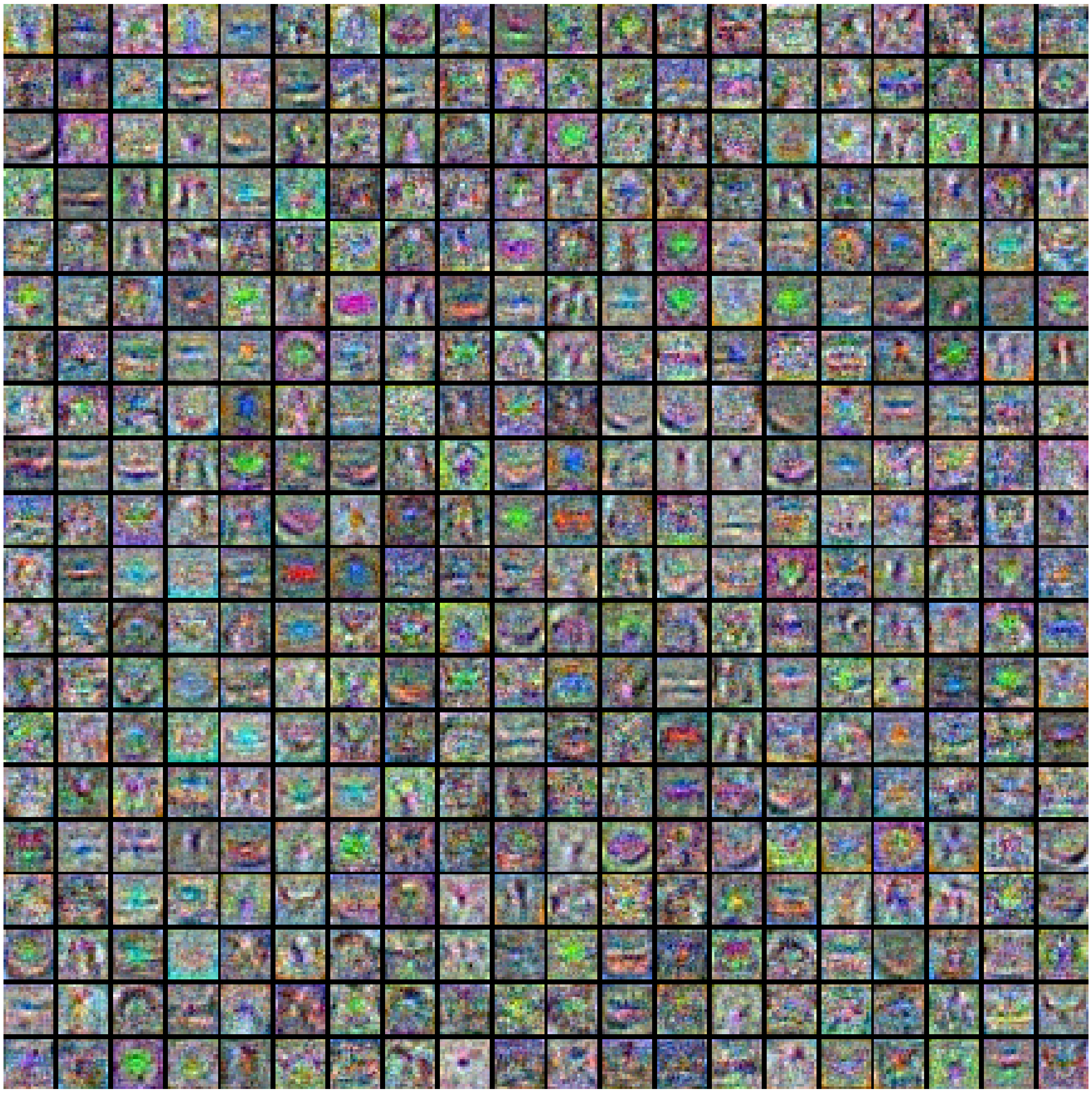
```
print('best validation accuracy achieved during cross-validation: %f' %␣
 ↪best_val)

# *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
```

```
hidden_size 400.000000 learn_rate 1.600000e-03 reg_str 1.000000e-02 train
accuracy: 0.628959 val accuracy: 0.517000
hidden_size 428.000000 learn_rate 1.600000e-03 reg_str 1.000000e-02 train
accuracy: 0.617592 val accuracy: 0.512000
best validation accuracy achieved during cross-validation: 0.517000
```

[15]:
```
# Print your validation accuracy: this should be above 48%
val_acc = (best_net.predict(X_val) == y_val).mean()
print('Validation accuracy: ', val_acc)
```

```
Validation accuracy:  0.517
```

[16]:
```
# Visualize the weights of the best network
show_net_weights(best_net)
```



10 Run on the test set

When you are done experimenting, you should evaluate your final trained network on the test set; you should get above 48%.

[17]:
```
# Print your test accuracy: this should be above 48%
test_acc = (best_net.predict(X_test) == y_test).mean()
print('Test accuracy: ', test_acc)
```

```
Test accuracy:  0.525
```

Inline Question

Now that you have trained a Neural Network classifier, you may find that your testing accuracy is much lower than the training accuracy. In what ways can we decrease this gap? Select all that apply.

1. Train on a larger dataset.
2. Add more hidden units.
3. Increase the regularization strength.
4. None of the above.

$\color{blue}{\textit{YourAnswer}:}$ 1, 3 as this is asking about decreasing the gap not improving performance
$\color{blue}{\textit{YourExplanation}:}$ 1. True: Training on a larger dataset when working with NNs increases performance roughly logarithmically.

2. False: We know that as the complexity of a machine learning model increases, the more prone the model is to overfitting. This would mean that the gap between the two grows. However, adding more hidden units allows for better inference on a combinatorial basis. We know that to simulate a deeper NN, we can use a shallow NN with exponentially more neurons in the hidden layer and achieve better performance on the test set. Therefore, adding more hidden units could possibly shrink the gap at a certain point, especially for high-performing models where the training accuracy is around 100% and test is around 95%, as some have achieved with the CIFAR-10 dataset.

3. True: This will lead to a higher bias scenario that will cause the gap to shrink, but may also negatively impact model performance, especially on the training set.

---

11 IMPORTANT

This is the end of this question. Please do the following:

1. Click `File -> Save` to make sure the latest checkpoint of this notebook is saved to your Drive.
2. Execute the cell below to download the modified `.py` files back to your drive.

[0]:
```
import os

FOLDER_TO_SAVE = os.path.join('drive/My Drive/', FOLDERNAME)
FILES_TO_SAVE = ['cs231n/classifiers/neural_net.py']

for files in FILES_TO_SAVE:
  with open(os.path.join(FOLDER_TO_SAVE, '/'.join(files.split('/')[1:])), 'w')␣
 ↪as f:
    f.write(''.join(open(files).readlines()))
```

features

April 20, 2020

[1]:
```
from google.colab import drive

drive.mount('/content/drive', force_remount=True)

# enter the foldername in your Drive where you have saved the unzipped
# 'cs231n' folder containing the '.py', 'classifiers' and 'datasets'
# folders.
# e.g. 'cs231n/assignments/assignment1/cs231n/'
FOLDERNAME = 'CS231N/assignment1/cs231n/'

assert FOLDERNAME is not None, "[!] Enter the foldername."

%cd drive/My\ Drive
%cp -r $FOLDERNAME ../../
%cd ../../
%cd cs231n/datasets/
!bash get_datasets.sh
%cd ../../
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id
=947318989803-6bn6qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleusercontent.com&redire
ct_uri=urn%3aietf%3awg%3aoauth%3a2.0%3aoob&response_type=code&scope=email%20http
s%3a%2f%2fwww.googleapis.com%2fauth%2fdocs.test%20https%3a%2f%2fwww.googleapis.c
om%2fauth%2fdrive%20https%3a%2f%2fwww.googleapis.com%2fauth%2fdrive.photos.reado
nly%20https%3a%2f%2fwww.googleapis.com%2fauth%2fpeopleapi.readonly

Enter your authorization code:
ůůůůůůůůůů
Mounted at /content/drive
/content/drive/My Drive
/content
/content/cs231n/datasets
--2020-04-17 22:49:00--  http://www.cs.toronto.edu/~kriz/cifar-10-python.tar.gz
Resolving www.cs.toronto.edu (www.cs.toronto.edu)... 128.100.3.30
Connecting to www.cs.toronto.edu (www.cs.toronto.edu)|128.100.3.30|:80...
connected.
HTTP request sent, awaiting response... 200 OK
```

```
Length: 170498071 (163M) [application/x-gzip]
Saving to: cifar-10-python.tar.gz

cifar-10-python.tar 100%[===================>] 162.60M  47.3MB/s    in 3.6s

2020-04-17 22:49:03 (44.7 MB/s) - cifar-10-python.tar.gz saved
[170498071/170498071]

cifar-10-batches-py/
cifar-10-batches-py/data_batch_4
cifar-10-batches-py/readme.html
cifar-10-batches-py/test_batch
cifar-10-batches-py/data_batch_3
cifar-10-batches-py/batches.meta
cifar-10-batches-py/data_batch_2
cifar-10-batches-py/data_batch_5
cifar-10-batches-py/data_batch_1
/content
```

1 Image features exercise

Complete and hand in this completed worksheet (including its outputs and any supporting code outside of the worksheet) with your assignment submission. For more details see the assignments page on the course website.

We have seen that we can achieve reasonable performance on an image classification task by training a linear classifier on the pixels of the input image. In this exercise we will show that we can improve our classification performance by training linear classifiers not on raw pixels but on features that are computed from the raw pixels.

All of your work for this exercise will be done in this notebook.

[0]:
```
import random
import numpy as np
from cs231n.data_utils import load_CIFAR10
import matplotlib.pyplot as plt



%matplotlib inline
plt.rcParams['figure.figsize'] = (10.0, 8.0) # set default size of plots
plt.rcParams['image.interpolation'] = 'nearest'
plt.rcParams['image.cmap'] = 'gray'

# for auto-reloading extenrnal modules
# see http://stackoverflow.com/questions/1907993/
 ↪autoreload-of-modules-in-ipython
%load_ext autoreload
%autoreload 2
```

1.1 Load data

Similar to previous exercises, we will load CIFAR-10 data from disk.

[0]:
```
from cs231n.features import color_histogram_hsv, hog_feature

def get_CIFAR10_data(num_training=49000, num_validation=1000, num_test=1000):
    # Load the raw CIFAR-10 data
    cifar10_dir = 'cs231n/datasets/cifar-10-batches-py'

    # Cleaning up variables to prevent loading data multiple times (which may␣
 ↪cause memory issue)
    try:
       del X_train, y_train
       del X_test, y_test
       print('Clear previously loaded data.')
    except:
       pass

    X_train, y_train, X_test, y_test = load_CIFAR10(cifar10_dir)

    # Subsample the data
    mask = list(range(num_training, num_training + num_validation))
    X_val = X_train[mask]
    y_val = y_train[mask]
    mask = list(range(num_training))
    X_train = X_train[mask]
    y_train = y_train[mask]
    mask = list(range(num_test))
    X_test = X_test[mask]
    y_test = y_test[mask]

    return X_train, y_train, X_val, y_val, X_test, y_test

X_train, y_train, X_val, y_val, X_test, y_test = get_CIFAR10_data()
```

1.2 Extract Features

For each image we will compute a Histogram of Oriented Gradients (HOG) as well as a color histogram using the hue channel in HSV color space. We form our final feature vector for each image by concatenating the HOG and color histogram feature vectors.

Roughly speaking, HOG should capture the texture of the image while ignoring color information, and the color histogram represents the color of the input image while ignoring texture. As a result, we expect that using both together ought to work better than using either alone. Verifying this assumption would be a good thing to try for your own interest.

The `hog_feature` and `color_histogram_hsv` functions both operate on a single image and return a feature vector for that image. The extract_features function takes a set of images and a list of feature functions and evaluates each feature function on each image, storing the results in a matrix where each column is the concatenation of all feature vectors for a single image.

[4]:
```
from cs231n.features import *

num_color_bins = 10 # Number of bins in the color histogram
feature_fns = [hog_feature, lambda img: color_histogram_hsv(img,␣
 ↪nbin=num_color_bins)]
X_train_feats = extract_features(X_train, feature_fns, verbose=True)
X_val_feats = extract_features(X_val, feature_fns)
X_test_feats = extract_features(X_test, feature_fns)

# Preprocessing: Subtract the mean feature
mean_feat = np.mean(X_train_feats, axis=0, keepdims=True)
X_train_feats -= mean_feat
X_val_feats -= mean_feat
X_test_feats -= mean_feat

# Preprocessing: Divide by standard deviation. This ensures that each feature
# has roughly the same scale.
std_feat = np.std(X_train_feats, axis=0, keepdims=True)
X_train_feats /= std_feat
X_val_feats /= std_feat
X_test_feats /= std_feat

# Preprocessing: Add a bias dimension
X_train_feats = np.hstack([X_train_feats, np.ones((X_train_feats.shape[0], 1))])
X_val_feats = np.hstack([X_val_feats, np.ones((X_val_feats.shape[0], 1))])
X_test_feats = np.hstack([X_test_feats, np.ones((X_test_feats.shape[0], 1))])
```

```
Done extracting features for 1000 / 49000 images
Done extracting features for 2000 / 49000 images
Done extracting features for 3000 / 49000 images
Done extracting features for 4000 / 49000 images
Done extracting features for 5000 / 49000 images
Done extracting features for 6000 / 49000 images
Done extracting features for 7000 / 49000 images
Done extracting features for 8000 / 49000 images
Done extracting features for 9000 / 49000 images
Done extracting features for 10000 / 49000 images
Done extracting features for 11000 / 49000 images
Done extracting features for 12000 / 49000 images
Done extracting features for 13000 / 49000 images
Done extracting features for 14000 / 49000 images
Done extracting features for 15000 / 49000 images
Done extracting features for 16000 / 49000 images
Done extracting features for 17000 / 49000 images
Done extracting features for 18000 / 49000 images
Done extracting features for 19000 / 49000 images
```

```
Done extracting features for 20000 / 49000 images
Done extracting features for 21000 / 49000 images
Done extracting features for 22000 / 49000 images
Done extracting features for 23000 / 49000 images
Done extracting features for 24000 / 49000 images
Done extracting features for 25000 / 49000 images
Done extracting features for 26000 / 49000 images
Done extracting features for 27000 / 49000 images
Done extracting features for 28000 / 49000 images
Done extracting features for 29000 / 49000 images
Done extracting features for 30000 / 49000 images
Done extracting features for 31000 / 49000 images
Done extracting features for 32000 / 49000 images
Done extracting features for 33000 / 49000 images
Done extracting features for 34000 / 49000 images
Done extracting features for 35000 / 49000 images
Done extracting features for 36000 / 49000 images
Done extracting features for 37000 / 49000 images
Done extracting features for 38000 / 49000 images
Done extracting features for 39000 / 49000 images
Done extracting features for 40000 / 49000 images
Done extracting features for 41000 / 49000 images
Done extracting features for 42000 / 49000 images
Done extracting features for 43000 / 49000 images
Done extracting features for 44000 / 49000 images
Done extracting features for 45000 / 49000 images
Done extracting features for 46000 / 49000 images
Done extracting features for 47000 / 49000 images
Done extracting features for 48000 / 49000 images
Done extracting features for 49000 / 49000 images
```

1.3 Train SVM on features

Using the multiclass SVM code developed earlier in the assignment, train SVMs on top of the features extracted above; this should achieve better results than training SVMs directly on top of raw pixels.

[34]:
```python
# Use the validation set to tune the learning rate and regularization strength

from cs231n.classifiers.linear_classifier import LinearSVM

learning_rates = [0.5e-8, 0.6e-8, 1e-8]
regularization_strengths = [5e6, 5.15e6, 5.2e6] #5e4, 5e5, 5e6]

results = {}
best_val = -1
best_svm = None
```

```
################################################################################
# TODO:                                                                        #
# Use the validation set to set the learning rate and regularization strength. #
# This should be identical to the validation that you did for the SVM; save    #
# the best trained classifer in best_svm. You might also want to play          #
# with different numbers of bins in the color histogram. If you are careful    #
# you should be able to get accuracy of near 0.44 on the validation set.       #
################################################################################
# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

for r in regularization_strengths:
    for l in learning_rates:
        svm = LinearSVM();
        loss_hist = svm.train(X_train_feats, y_train, l, r, num_iters=3000)
        y_train_pred = svm.predict(X_train_feats)
        y_val_pred = svm.predict(X_val_feats)
        train_accuracy = np.mean(y_train_pred == y_train)
        val_accuracy = np.mean(y_val_pred == y_val)
        results[(l, r)] = train_accuracy, val_accuracy
        if val_accuracy > best_val:
            best_val = val_accuracy
            best_svm = svm

# *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****

# Print out results.
for lr, reg in sorted(results):
    train_accuracy, val_accuracy = results[(lr, reg)]
    print('lr %e reg %e train accuracy: %f val accuracy: %f' % (
                lr, reg, train_accuracy, val_accuracy))

print('best validation accuracy achieved during cross-validation: %f' % best_val)
```

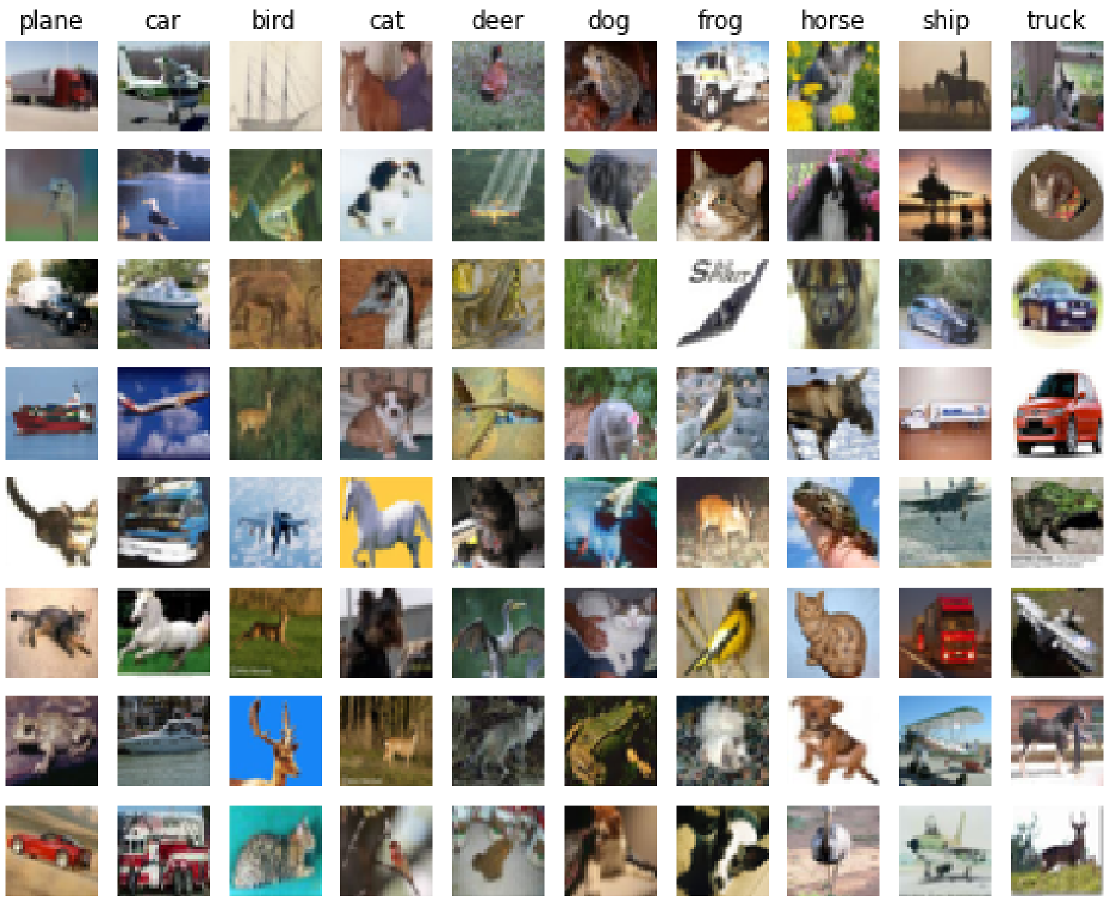
```
lr 5.000000e-09 reg 5.000000e+06 train accuracy: 0.406000 val accuracy: 0.401000
lr 5.000000e-09 reg 5.150000e+06 train accuracy: 0.418510 val accuracy: 0.431000
lr 5.000000e-09 reg 5.200000e+06 train accuracy: 0.410367 val accuracy: 0.406000
lr 6.000000e-09 reg 5.000000e+06 train accuracy: 0.411510 val accuracy: 0.414000
lr 6.000000e-09 reg 5.150000e+06 train accuracy: 0.409673 val accuracy: 0.416000
lr 6.000000e-09 reg 5.200000e+06 train accuracy: 0.408041 val accuracy: 0.404000
lr 1.000000e-08 reg 5.000000e+06 train accuracy: 0.413898 val accuracy: 0.395000
```

```
lr 1.000000e-08 reg 5.150000e+06 train accuracy: 0.409531 val accuracy: 0.412000
lr 1.000000e-08 reg 5.200000e+06 train accuracy: 0.415204 val accuracy: 0.424000
best validation accuracy achieved during cross-validation: 0.431000
```

[35]:
```
# Evaluate your trained SVM on the test set: you should be able to get at least␣
↪0.40
y_test_pred = best_svm.predict(X_test_feats)
test_accuracy = np.mean(y_test == y_test_pred)
print(test_accuracy)
```

```
0.422
```

[36]:
```
# An important way to gain intuition about how an algorithm works is to
# visualize the mistakes that it makes. In this visualization, we show examples
# of images that are misclassified by our current system. The first column
# shows images that our system labeled as "plane" but whose true label is
# something other than "plane".

examples_per_class = 8
classes = ['plane', 'car', 'bird', 'cat', 'deer', 'dog', 'frog', 'horse',␣
↪'ship', 'truck']
for cls, cls_name in enumerate(classes):
    idxs = np.where((y_test != cls) & (y_test_pred == cls))[0]
    idxs = np.random.choice(idxs, examples_per_class, replace=False)
    for i, idx in enumerate(idxs):
        plt.subplot(examples_per_class, len(classes), i * len(classes) + cls +␣
↪1)
        plt.imshow(X_test[idx].astype('uint8'))
        plt.axis('off')
        if i == 0:
            plt.title(cls_name)
plt.show()
```



1.3.1 Inline question 1:

Describe the misclassification results that you see. Do they make sense?

Your Answer : Many of the misclassification results come from photos with atypical positioning or color grating. For example, the first misclassified photo under dog (it's actually a frog) makes sense from afar because it's seated in a way that a dog would be. The color grating also plays a role as seen with the second-to-last misclassified bird photo (it's actually a deer). The background of the photo is bright blue, as one would see in a photo of a flying bird. In addition, the antlers are posed in a way such that they could pass as wings, and the color of the deer is also a reasonable color for a bird. Therefore to me, the majority of these misclassifications are understandable.

1.4 Neural Network on image features

Earlier in this assigment we saw that training a two-layer neural network on raw pixels achieved better classification performance than linear classifiers on raw pixels. In this notebook we have seen that linear classifiers on image features outperform linear classifiers on raw pixels.

For completeness, we should also try training a neural network on image features. This approach should outperform all previous approaches: you should easily be able to achieve over 55% classification accuracy on the test set; our best model achieves about 60% classification accuracy.

[38]:
```
# Preprocessing: Remove the bias dimension
# Make sure to run this cell only ONCE
print(X_train_feats.shape)
X_train_feats = X_train_feats[:, :-1]
X_val_feats = X_val_feats[:, :-1]
X_test_feats = X_test_feats[:, :-1]

print(X_train_feats.shape)
```

```
(49000, 155)
(49000, 154)
```

[54]:
```
from cs231n.classifiers.neural_net import TwoLayerNet

input_dim = X_train_feats.shape[1]
hidden_dim = 500
num_classes = 10

net = TwoLayerNet(input_dim, hidden_dim, num_classes)
best_net = None

################################################################################
# TODO: Train a two-layer neural network on image features. You may want to   ␣
↪#
# cross-validate various parameters as in previous sections. Store your best  ␣
↪#
# model in the best_net variable.                                              ␣
↪#
################################################################################
# *****START OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
best_val = 0.0
hidden_size = [450, 500, 550]
learning_rates = [0.6, 0.7, 0.8]
regularization_strengths = [0.1e-2, 0.5e-2, 1e-2]

for h in hidden_size:
    for l in learning_rates:
        for r in regularization_strengths:
          nn = TwoLayerNet(input_dim, h, num_classes)
          nn.train(X_train_feats, y_train, X_val_feats, y_val, learning_rate=l,␣
↪reg=r, num_iters=1000)
          y_train_pred = nn.predict(X_train_feats)
          y_val_pred = nn.predict(X_val_feats)
          train_accuracy = np.mean(y_train_pred == y_train)
          val_accuracy = np.mean(y_val_pred == y_val)
          results[(h, l, r)] = train_accuracy, val_accuracy
```

```
        print('hidden_size %f learn_rate %e reg_str %e train accuracy: %f val␣
↪accuracy: %f' % (h,
              l, r, train_accuracy, val_accuracy))

        if val_accuracy > best_val:
            best_val = val_accuracy
            best_net = nn

print('best validation accuracy achieved during cross-validation: %f' %␣
↪best_val)

# *****END OF YOUR CODE (DO NOT DELETE/MODIFY THIS LINE)*****
```

```
hidden_size 450.000000 learn_rate 6.000000e-01 reg_str 1.000000e-03 train
accuracy: 0.624184 val accuracy: 0.573000
hidden_size 450.000000 learn_rate 6.000000e-01 reg_str 5.000000e-03 train
accuracy: 0.551306 val accuracy: 0.534000
hidden_size 450.000000 learn_rate 6.000000e-01 reg_str 1.000000e-02 train
accuracy: 0.507224 val accuracy: 0.504000
hidden_size 450.000000 learn_rate 7.000000e-01 reg_str 1.000000e-03 train
accuracy: 0.625878 val accuracy: 0.562000
hidden_size 450.000000 learn_rate 7.000000e-01 reg_str 5.000000e-03 train
accuracy: 0.550367 val accuracy: 0.535000
hidden_size 450.000000 learn_rate 7.000000e-01 reg_str 1.000000e-02 train
accuracy: 0.502163 val accuracy: 0.467000
hidden_size 450.000000 learn_rate 8.000000e-01 reg_str 1.000000e-03 train
accuracy: 0.634265 val accuracy: 0.571000
hidden_size 450.000000 learn_rate 8.000000e-01 reg_str 5.000000e-03 train
accuracy: 0.551735 val accuracy: 0.508000
hidden_size 450.000000 learn_rate 8.000000e-01 reg_str 1.000000e-02 train
accuracy: 0.504653 val accuracy: 0.520000
hidden_size 500.000000 learn_rate 6.000000e-01 reg_str 1.000000e-03 train
accuracy: 0.612612 val accuracy: 0.565000
hidden_size 500.000000 learn_rate 6.000000e-01 reg_str 5.000000e-03 train
accuracy: 0.550510 val accuracy: 0.532000
hidden_size 500.000000 learn_rate 6.000000e-01 reg_str 1.000000e-02 train
accuracy: 0.505429 val accuracy: 0.491000
hidden_size 500.000000 learn_rate 7.000000e-01 reg_str 1.000000e-03 train
accuracy: 0.632490 val accuracy: 0.580000
hidden_size 500.000000 learn_rate 7.000000e-01 reg_str 5.000000e-03 train
accuracy: 0.550898 val accuracy: 0.537000
hidden_size 500.000000 learn_rate 7.000000e-01 reg_str 1.000000e-02 train
accuracy: 0.499837 val accuracy: 0.490000
hidden_size 500.000000 learn_rate 8.000000e-01 reg_str 1.000000e-03 train
accuracy: 0.626837 val accuracy: 0.561000
hidden_size 500.000000 learn_rate 8.000000e-01 reg_str 5.000000e-03 train
accuracy: 0.554980 val accuracy: 0.513000
```

```
hidden_size 500.000000 learn_rate 8.000000e-01 reg_str 1.000000e-02 train
accuracy: 0.501857 val accuracy: 0.511000
hidden_size 550.000000 learn_rate 6.000000e-01 reg_str 1.000000e-03 train
accuracy: 0.631265 val accuracy: 0.573000
hidden_size 550.000000 learn_rate 6.000000e-01 reg_str 5.000000e-03 train
accuracy: 0.560265 val accuracy: 0.556000
hidden_size 550.000000 learn_rate 6.000000e-01 reg_str 1.000000e-02 train
accuracy: 0.507776 val accuracy: 0.497000
hidden_size 550.000000 learn_rate 7.000000e-01 reg_str 1.000000e-03 train
accuracy: 0.626245 val accuracy: 0.560000
hidden_size 550.000000 learn_rate 7.000000e-01 reg_str 5.000000e-03 train
accuracy: 0.546735 val accuracy: 0.517000
hidden_size 550.000000 learn_rate 7.000000e-01 reg_str 1.000000e-02 train
accuracy: 0.499388 val accuracy: 0.484000
hidden_size 550.000000 learn_rate 8.000000e-01 reg_str 1.000000e-03 train
accuracy: 0.637429 val accuracy: 0.557000
hidden_size 550.000000 learn_rate 8.000000e-01 reg_str 5.000000e-03 train
accuracy: 0.559265 val accuracy: 0.541000
hidden_size 550.000000 learn_rate 8.000000e-01 reg_str 1.000000e-02 train
accuracy: 0.489367 val accuracy: 0.480000
best validation accuracy achieved during cross-validation: 0.580000
```

[55]:
```
# Run your best neural net classifier on the test set. You should be able
# to get more than 55% accuracy.

test_acc = (best_net.predict(X_test_feats) == y_test).mean()
print(test_acc)
```

```
0.564
```

---

2 IMPORTANT

This is the end of this question. Please do the following:

1. Click `File -> Save` to make sure the latest checkpoint of this notebook is saved to your Drive.
2. Execute the cell below to download the modified .py files back to your drive.

[0]:
```
import os

FOLDER_TO_SAVE = os.path.join('drive/My Drive/', FOLDERNAME)
FILES_TO_SAVE = []

for files in FILES_TO_SAVE:
```

```
with open(os.path.join(FOLDER_TO_SAVE, '/'.join(files.split('/')[1:])), 'w')␣
↪as f:
    f.write(''.join(open(files).readlines()))
```